THE IMPACT OF MEDICARE READMISSION REDUCTION POLICIES ON PATIENTS, PRIMARY CARE PRACTICES, AND HOSPITALS

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A dissertation submitted to the faculty at the University of North Carolina at Chapel Hill in partial fulfillment of the requirements for the degree of Doctor of Philosophy in the Department of Health Policy and Management in the Gillings School of Global Public Health.

Chapel Hill
2020

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ABSTRACT

Steven Benjamin Spivack: The Impact of Medicare Readmission Reduction Policies on Patients, Primary Care Practices, and Hospitals
(Under the direction of Jonathan Oberlander)

Objective: To evaluate the impact of Medicare's readmission reduction policies on patients, primary care practices, and hospitals.

Methods: I employed distinct methods to examine the effect of Medicare's readmission reduction policies on each of the three groups identified in my objective. For patients, I used 2007-2014 admission-level data from California, Florida, and New York to create triple differences models investigating whether the Hospital Readmissions Reduction Program led to spillover for Medicare Advantage patients. For primary care practices, I combined the 2017-2018 National Survey of Healthcare Organizations and Systems with 100% 2015-2016 Medicare claims data to assess the relationship between practices' readmission reduction activities and readmission rates for their patients using both mixed effects and linear regression models. For hospitals, I merged 2013-2018 *Hospital Compare* data and CMS's annual impact files for the same timeframe to estimate fixed effects models to examine whether hospitals facing potentially larger readmission payment penalties had fewer excess readmissions.

Results: Readmission rates for Medicare Advantage patients dropped by one percentage point for acute myocardial infarction ($P < .001$) and half a percentage point for heart failure ($P < .01$) after the implementation of the Hospital Readmissions

Reduction Program, indicating the presence of spillover. Primary care practices' number of readmission reduction activities was significantly associated ($P < .05$) with lower readmission rates. On average, practices experienced a 0.05 percentage point decrease in readmission rates for each additional activity. Hospitals facing larger potential readmission payment penalties did not have significantly fewer excess readmissions.

Conclusions: The Hospital Readmissions Reduction Program led to significant declines in readmission rates for Medicare Advantage patients, whom comprise a growing share of Medicare enrollees. Primary care practices might be able to lower readmission rates for their patients by engaging in large numbers of readmission reduction activities. Finally, while the financial incentives associated with the Hospital Readmissions Reduction Program may have acted as a triggering mechanism to signal hospitals on the need to reduce readmissions, I did not observe a direct relationship between the size of the incentive and performance on readmissions

To my son Micah, je t’aime.

ACKNOWLEDGEMENTS

I owe an enormous debt of gratitude to all who supported me throughout this journey. My advisor, Jonathan Oberlander, could not have been a better mentor or friend, even if he is a Patriots fan. The rest of my committee, Kristin Reiter, Morris Weinberger, Justin Trogdon, and Darren DeWalt provided invaluable feedback and guidance. Without their help, none of this would have been possible. I am forever grateful to Valerie Lewis, a friend and mentor, who was always there to support me academically and emotionally.

To my PhD cohort, and the rest of my colleagues, I could not have completed the coursework, comprehensive exams, and dissertation without them. I consider them all a member of my extended family and I cannot imagine sharing this experience with a better group of academics and friends. I want to especially thank Alexis Kirk and Lindsey Yates who always knew how to cheer me up when I needed it the most.

To my family, thank you for everything. My mother taught me so much and I would not be here without her love and encouragement. My father constantly sacrificed to make it possible for me to pursue my dreams and demonstrated the importance of hard work and ambition. My brothers, Eric and Jeff, have always protected me as older siblings do, and the way they raise their children is a constant source of inspiration. My in-laws, Esther and Larry, treat me as their own and words cannot express how grateful

I am for their love. My other brothers, Kevin, Josh, George, and Raf, their friendship means the world to me and I would not be here today without them.

To my wife Miriam, this degree is just as much hers as it is mine. She has given me the two greatest gifts I have ever received, her love and our son. I have faced several difficult challenges during this process, both physical and emotional, and her encouragement made the impossible possible. To my son, Micah, his laughter, joy, and hugs are worth more than any degree or sum of money.

This dissertation was supported by the National Center for Advancing Translational Sciences, National Institutes of Health, through Grant Award Number TL1TR001110. The content is solely the responsibility of the authors and does not necessarily represent the official views of the NIH.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF ABBREVIATIONS

AMI	Acute Myocardial Infarction
APM	Alternative Payment Model
CMS	Centers for Medicare and Medicaid Services
DSH	Disproportionate Share Hospital
ERR	Excess Readmissions Ratio
HCC	Hierarchical Condition Category
HF	Heart Failure
HRRP	Hospital Readmissions Reduction Program
MA	Medicare Advantage
MIPS	Merit-based Incentive Payment System
NSHOS	National Survey of Healthcare Organizations and Systems
NTC	Non-Targeted Condition
P4P	Pay-for-Performance
PCP	Primary Care Practice
PN	Pneumonia
QPP	Quality Payment Program
RSRR	Risk-Standardized Readmission Rate
SID	State Inpatient Databases
TM	Traditional Medicare

CHAPTER 1. INTRODUCTION

Background

Hospital readmissions have long been recognized as important markers of both quality and resource use.[1,2] In response to mounting concerns about readmissions, federal policymakers have introduced readmission measures into pay-for-performance (P4P) and value-based purchasing programs for Traditional Medicare (TM) beneficiaries. The 2010 Hospital Readmissions Reduction Program (HRRP), part of the Affordable Care Act, represented a milestone in such efforts.[3] Since then, Medicare has expanded the number and types of readmission measures as part of its payment reforms. In addition to hospitals, Medicare readmission measures now encompass skilled nursing facilities,[4] home health care agencies,[5] dialysis facilities,[6] physicians and practices,[7] and accountable care organizations.[8]

The rise of Medicare readmission reduction policies has led to a burgeoning literature on readmissions. Almost all of this research has focused on the effects of the HRRP, since Medicare programs targeting other areas of the health system are much newer and have yet to be fully implemented. There is also a smaller, but expanding, subset of articles that examine the types of activities providers can implement that may help reduce readmissions. Below I summarize the findings from the literature and the contribution of my dissertation to the field.

Much of the evidence regarding the HRRP's impact on readmissions suggests that the program significantly reduced readmission rates for Medicare patients.[9,10] As a result, the Medicare Payment Advisory Commission has declared the HRRP a "success."[11] The majority of these reductions were experienced by TM beneficiaries admitted for the three conditions initially targeted by the HRRP: acute myocardial infarction (AMI), heart failure (HF), and pneumonia (PN).[12] Depending on the study, the HRRP has been credited with causing a drop in readmission rates of one to three percentage points for each of these three conditions.[10,12–15] Additional research indicates that the HRRP also caused readmission rates to fall for other groups of patients. This includes TM beneficiaries hospitalized for conditions not targeted by the HRRP,[9,15–18] privately insured persons,[15,18–20] and Medicaid enrollees.[9,20]

The findings above suggest that the HRRP is the reason for patients experiencing lower readmission rates. However, more recent work has called that conclusion into question. While these studies do not deny an overall drop in readmissions since the HRRP's introduction, they contend that too much credit has been given to the program. One possible explanation for the drop in readmission rates after the HRRP's implementation could be regression to the mean.[21] Joshi et al. argue that most of the decline in readmission was driven by hospitals with the highest readmission rates, which they contend would have occurred irrespective of the HRRP. Thus, random chance, and not the HRRP, could explain lower readmission rates following the HRRP's introduction.

The HRRP's effect may also be overstated due to changes in coding patterns.[22] Ody et al. found that readmission rates dropped the most for hospitals coding a larger number of secondary diagnoses for admitted patients. Hospitals were able to increase the number of secondary diagnoses in claims because of another policy that was introduced around the same time as HRRP's enactment. Readmission rates may also have declined due to increases in observation stays.[23] Observation stays do not count as readmissions, and hospitals could be using them to treat patients without formally admitting them. Although observation stays have risen since the introduction of the HRRP, they have not risen enough to completely explain away lower readmission rates during this period.[10]

There are also concerns about the trajectory of HRRP. The declines in hospital readmissions for Medicare beneficiaries came largely in the program's first few years. Newer years of data indicate a plateauing of readmission rates for Medicare patients since 2017.[9,10,24] Earlier declines in readmissions thus may not be sustainable and it is uncertain whether the HRRP can achieve additional reductions in coming years.

Beyond the possibility that the HRRP's success has been overstated, there are also concerns regarding unintended consequences. Recent work by Wadhera et al. and Samarghandi and Qayyum suggests that patients admitted for conditions targeted by the HRRP may be experiencing increases in mortality rates.[25,26] Hospitals delaying or avoiding readmitting patients in order to reduce readmissions could lead to deaths for some patients. However, the literature on this topic is inconclusive with other studies refuting this finding.[24,27] Nevertheless, Medicare has publicly stated it is "committed to monitoring" this topic in case the HRRP is causing an increase in mortality rates.[28]

Another unintended consequence that has garnered much attention is the fact that the HRRP appears to be disproportionately penalizing hospitals that care for more low socioeconomic status (SES) patients. While the measures in the HRRP adjust for patients' clinical factors, they do not account for SES variables like race, income, or education. These variables are important in predicting readmission, even when accounting for baseline comorbidities.[29,30] As a result, safety-net hospitals and hospitals caring for more minorities or dual-eligible patients have received disproportionately higher HRRP payment penalties.[31–34] While readmission rates for hospitals caring for more low-SES patients have declined since the HRRP's introduction, reductions have not matched the pace of hospitals caring for fewer low-SES patients. [35,36] Since hospitals have little control over their patient mix, a more equitable approach to the HRRP measures would to adjust for patient SES.[37] Medicare was initially unwilling to adjust HRRP measures for SES but has since compromised to only compare readmission rates for hospitals caring for similar proportions of dual-eligible patients. As a result, the gap in payment penalties between hospitals caring for fewer or more low-SES patients has shrunk substantially, although not completely.[38]

Lastly, because of the increased attention to readmissions by providers, payers, and policymakers, there has also been a rise in research on the topic of how to reduce readmissions. This field originated with the care transitions literature which investigates how to reduce readmissions across episodes of care.[39–41] These are largely multi-component interventions that demonstrated the effectiveness of care managers, proper discharge planning, medication reconciliation, conducting home visits, along with several other tasks, as a group of activities that could help reduce readmission rates when they are combined in a single package. After the HRRP's enactment, much of the work in this field then shifted to identifying activities and strategies that could be implemented at the hospital level, especially care transitions interventions. [42–44] Hospitals that performed the best on readmissions did so by implementing as many of these activities as possible.[45]

Even with this rather deep research pool on the topic of readmissions, there still remain important gaps that have not been addressed. Specifically, three topics have not received nearly as much attention as those cited above. First, we still know very little about how the size and structure of the HRRP's payment penalties influence hospitals' performance on readmissions. Second, while there have been numerous studies examining HRRP spillover, almost all of these studies have focused on privately insured or TM patients. Much less is known about spillover for Medicare Advantage (MA) patients, who are not subject to the HRRP. Third, while we know a lot about the types of strategies hospitals can use to reduce readmissions, little is known about how primary care practices (PCPs) can lower readmission rates for their patients. PCPs play an important role in reducing readmissions, and the inclusion of a readmission measure in the Quality Payment Program (QPP) means that these practices may face payment adjustments depending on their readmission performance.

The purpose of this dissertation is to examine these gaps in the readmission reduction literature. In doing so, I aim to shed light on: 1) how financial incentives may impact hospital readmissions; 2) the effects of the HRRP on MA patients; and 3) the types of PCP activities that might help reduce readmission rates. While each of these topics are unique, they are all motivated by advancing our understanding of the impact of Medicare readmission policies on patients, practices, and hospitals.

Next, I provide a high-level summary of each of my three aims. I briefly describe the significance and contribution of each aim, detail my hypothesis and conceptual model, and review my methods and main findings.

Aim 1: The Role of Incentive Size when Paying for Performance: The Hospital Readmissions Reduction Program

Significance and Contribution

We know from prior studies that the impact of financial incentives in health care is mixed at best.[46,47] Yet Medicare, among other payers, has embraced the concept of P4P in a variety of value-based purchasing programs. One of Medicare's most well-known P4P programs is the HRRP. It reduces hospitals' Medicare reimbursement rates by up to three percent based on their number of excess readmissions for select conditions.[3] While the HRRP has been touted as a success by Medicare administrators and policy analysts because of declines in Medicare readmission rates that followed its introduction,[10,48,49] it remains unclear how much of this success was due to the size of the HRRP's payment penalties. We do not know whether hospitals facing larger potential penalties because they care for more Medicare patients reduce readmissions more than hospitals facing smaller penalties. This aim addresses that gap and thereby adds to the literature on the HRRP as well as the larger P4P evidence base examining the relationship between financial incentives and performance.

Central Hypothesis

I expect a significant negative relationship between the size of a hospital's HRRP payment penalty and their AMI, HF, and PN Excess Readmission Ratios (ERRs). I hypothesize that hospitals' ERRs will drop as their maximum potential HRRP payment penalty per admission rises.

Conceptual Model

The conceptual model for this aim is RAND's Value-Based Purchasing Conceptual Framework (Figure 1).[50] I rely on this model to examine how the HRRP's negative payment adjustments impact the intermediate effects of the program, which I define as reducing excess readmissions. I test my hypothesis that this relationship is mediated by the potential size of hospitals' negative payment adjustments. The strength of this relationship increases as Medicare consumes a larger proportion of a hospital's payer mix, which is represented by the "mix of populations served" bullet in the "characteristics of providers and practice settings" box in Figure 1. The conceptual model also details other provider characteristics that can influence the relationship between the HRRP's payment adjustments and hospital performance on readmissions. The model thus informs my decisions regarding the types of variables to adjust for in my analyses.

Data Source

I use two publicly available datasets for the years 2013-2018 in order to examine the relationship between hospitals' potential maximum HRRP payment adjustments and their performance on readmissions. The first is the *Hospital Compare* website, which publishes information on each hospital's rate of excess readmissions. The second is CMS's annual impact files, which include information on hospital payer mix as well as provider characteristics like teaching status and number of beds. I merge these two data sources using the Provider ID variable for each hospital.

Sample

I include hospitals that are subject to the HRRP, specifically, short-term acute-care inpatient hospitals. I then create hospital-level, condition-specific cohorts for AMI, HF, and PN. ERRs had to be present for a condition for all six years of data in order for a hospital to be included in a cohort. Thus, hospitals can be included in one condition cohort but not another if they were missing an ERR for at least one condition in one or more years of data.

Key Variables and Measures

My outcome for this aim is hospitals' ERR for the three conditions included since the beginning of the HRRP: AMI, HF, and PN. A ratio of one indicates average performance. A ratio below one signifies better performance and a ratio above one indicates worse performance. The further the ratio from one the stronger the indicator of good or poor performance. My independent variable is hospitals' maximum potential HRRP payment penalty per admission. This variable represents the maximum amount a hospital could be penalized based on their Medicare base DRG income for each year of data.

Data Analysis

I use fixed effects models to investigate the relationship between a hospital's maximum potential HRRP payment penalty per admission and their ERRs for AMI, HF, and PN. I run three models, one for each condition-cohort.

Main Findings

Unadjusted readmission rates dropped substantially for AMI, HF, and PN after the implementation of the HRRP. The majority of the decline in readmissions occurred between 2013-2016, with much more modest changes in 2017 and 2018. Facing potentially larger HRRP payment penalties per admission was not significantly associated with lower ERRs for AMI, HF, or PN. The fact that actual HRRP penalties are much smaller than the three percent maximum may explain why I did not observe a relationship between potential incentive size and performance on readmissions.

Aim 2: The Impact of The Hospital Readmissions Reduction Program on Medicare Advantage Patients: A Retrospective Study of Three Large States

Significance and Contribution

Since the HRRP's implementation, Medicare readmission rates have declined substantially for TM patients hospitalized for conditions targeted by the program.[10,12] There is also evidence of spillover as Medicare readmission rates have dropped for TM patients hospitalized for conditions not targeted by the program.[14,15] Moreover, privately insured and Medicaid patients have also experienced lower readmission rates since the implementation of the HRRP.[9,18] However, one patient population that has not been studied as extensively is MA enrollees. Although they are Medicare beneficiaries, the HRRP does not apply to them since they are not enrolled in TM. Therefore, this patient population serves as an important control group as they are more similar to the TM population in age and other characteristics than privately insured or Medicaid patients. Yet, few studies have investigated MA readmission rates since the HRRP's implementation, possibly because MA data can be more difficult to obtain. With MA enrollment projected to reach almost 50% by 2030 it is increasingly important to understand how TM policies are impacting MA patients.[51] This aim will advance our relatively scant knowledge of the HRRP's effects on MA patients by examining spillover effects for MA patients hospitalized in California, Florida, and New York. The findings will enable a richer understanding of the HRRP's effects on non-TM patient populations.

Central Hypothesis

The HRRP has also led to significant reductions in readmission rates for MA patients, indicating the presence of spillover effects.

Conceptual Model

This aim is based on the same conceptual model as the one I use in my first aim (Figure 1).[50] For this aim, the model elucidates how a program like the HRRP can also reduce readmission rates for other payers and populations due to the "spillover effects" bullet in the "intermediate effects" category. For the purposes of this aim, spillover effects are defined as reductions in readmission rates for MA patients. Similar to my first aim, this model also informs the types of covariates to include in models investigating spillover effects. In addition, the conceptual model displays external factors that can also lead to spillover effects. These examples of external factors are key when deciding on the proper control group to detect spillover effects.

Data Source

I use data from four sources to test my hypothesis. The first source is comprised of various State Inpatient Databases, which are 100% inpatient claims data made available by the Healthcare Cost and Utilization Project. For this study, I use New York and Florida data from 2007 through 2014 and California data from 2007-2011. Since California halted its participation in the State Inpatient Databases after 2011, I also obtain California's Patient Discharge Data from 2012-2014. These data are used to populate previous years of the State Inpatient Databases and also include 100% of inpatient claims. The final two datasets are the 2012-2014 Urban Influence Codes and the 2012-2014 American Community Survey owned by the Census Bureau in order to include additional socioeconomic variables present in State Inpatient Databases but not the Patient Discharge Data.

Sample

I include admissions for TM and MA patients 65 and older admitted to short-term, acute-care inpatient hospitals in California, New York, and Florida, between 2007-2014.

Key Variables and Measures

The outcome for this aim is unplanned 30-day readmissions. A readmission is defined as any unplanned hospitalization that occurs within 30 days of a previous index admission. Readmissions are categorized as dichotomous, meaning each index admission can have no more than one readmission. I distinguish between TM and MA admissions based on the primary expected payer variable.

Data Analysis

I construct triple difference-in-differences models to examine AMI, HF, and PN readmission rates for TM and MA admissions before and after implementation of the HRRP (2007-2011 vs. 2012-2014). I compare readmission rates for three groups of admissions, TM admissions for AMI, HF, or PN, TM admissions for non-targeted conditions (NTCs), and MA admissions for AMI, HF, or PN. I designated MA admissions for NTCs as the control group.

Main Findings

The HRRP resulted in significant spillover for MA readmission rates. MA patients admitted for AMI and HF experienced statistically significant declines in readmissions after the implementation of the HRRP. PN readmission rates for MA patients did not change significantly after the HRRP was implemented. The size of this effect depends on how much spillover is attributed to the control group, MA patients admitted for NTCs. The more the HRRP is credited for reducing MA NTC readmission rates the larger the spillover for AMI, HF, and PN readmission rates for MA patients.

Aim 3: The Association of Readmission Reduction Activities with Primary Care Practice Readmission Rates

Significance and Contribution

The increased emphasis on readmissions in health policy has led to novel research on the types of activities that can help to reduce readmissions. The majority of these studies has focused on hospital strategies associated with reducing readmissions, since hospitals have been the main target of Medicare's readmission reduction policies.[44,45] Yet hospitals are not the only care setting responsible for preventing patients from being readmitted. PCPs also play an integral role in this process. However, we know much less about the types of primary care activities that can help lower readmission rates for their patients.[52] While it is possible that many of the hospital-based strategies apply to a primary care setting, it is also conceivable that interventions that work in one care setting are not easily adapted in other settings.[53] Therefore, what remains to be tested is whether certain activities proven to be effective in hospitals can also help to reduce readmissions in PCPs. Not only is this question clinically relevant, it is also policy relevant since many practices face the possibility of payment adjustments due to poor performance on the readmission measure included in the QPP.[54] This aim will strengthen the readmission reduction strategies literature by providing additional evidence of the ways in which providers can influence their patients readmission rates.

Central Hypothesis

Engaging in more readmission reduction activities will be associated with lower PCP-level readmission rates.

Conceptual Model

I construct a conceptual model to illustrate the types of activities that PCPs can employ to reduce readmission rates for their patients (Figure 2). This model is based on prior literature demonstrating readmission reduction activities found to be effective in other care settings. The model is composed of activities in four care domains: 1) care management; 2) patient education; 3) addressing social needs; 4) using data for quality improvement. Practices are more likely to reduce their patients' readmission rates as they engage in more of these activities. Readmission rates are also influenced by patient and organizational factors outside of a practice's control.

Data Source

I use data from two sources. The first is the 2017-2018 National Survey of Healthcare Organizations and Systems. This is a survey of health systems, hospitals, and PCPs. For the purposes of this aim, I only use the practice survey. The survey used a stratified cluster sampling design to sample practices within and outside of health systems. The practice survey includes questions on a variety of topics, including care transitions and readmission reduction activities. I also use 100% Medicare claims data from 2015-2016 in order to assess practice-level readmission rates.

Sample

I include practices that responded to the survey that have at least 25 Medicare admissions during 2016. I include admissions for TM patients in these practices who are 65 and older admitted for any reason to a short-term, acute-care inpatient hospital.

Key Variables and Measures

The outcome for this aim is practices' risk-standardized readmission rate (RSRR). This is a continuous variable ranging from 0-100 that adjusts for patient and practice-level factors. The independent variable is practices' scores on a composite measure representing the number of readmission activities that a practice regularly conducts. This composite measure includes practices' responses on 12 readmission reduction activities. The composite score is standardized and ranges between 0-1, with higher scores indicating that a practice engages in more readmission reduction activities.

Data Analysis

I calculate practices readmission rates using a mixed-effects logistic regression model adjusting for patient race, income, frailty, and comorbidities. I then construct a linear regression model to examine the association between practices' readmission rates and their readmission reduction activities composite scores.

Main Findings

Practices' scores on the readmission reduction activities composite measure was significantly associated with lower RSRRs. Practices' RSRRs declined as they engaged in more of these activities. Practices employing more than 20 physicians, practices operating in urban areas, and practices caring for fewer dual-eligible patients also experienced lower RSRRs on average.

Organization of Dissertation

The rest of this dissertation is composed of three papers and a conclusion. Chapter 2 examines the relationship between the size and structure of the HRRP's payment penalties and hospital performance on readmissions. Chapter 3 investigates whether the HRRP has also lowered readmission rates for MA patients. Chapter 4 explores the relationship between PCPs' readmission reduction activities and their patients' readmission rates. Chapter 5 then summarizes my findings and details policy recommendations and areas for future research.

Figure 1. Conceptual Model for Aims 1 and 2

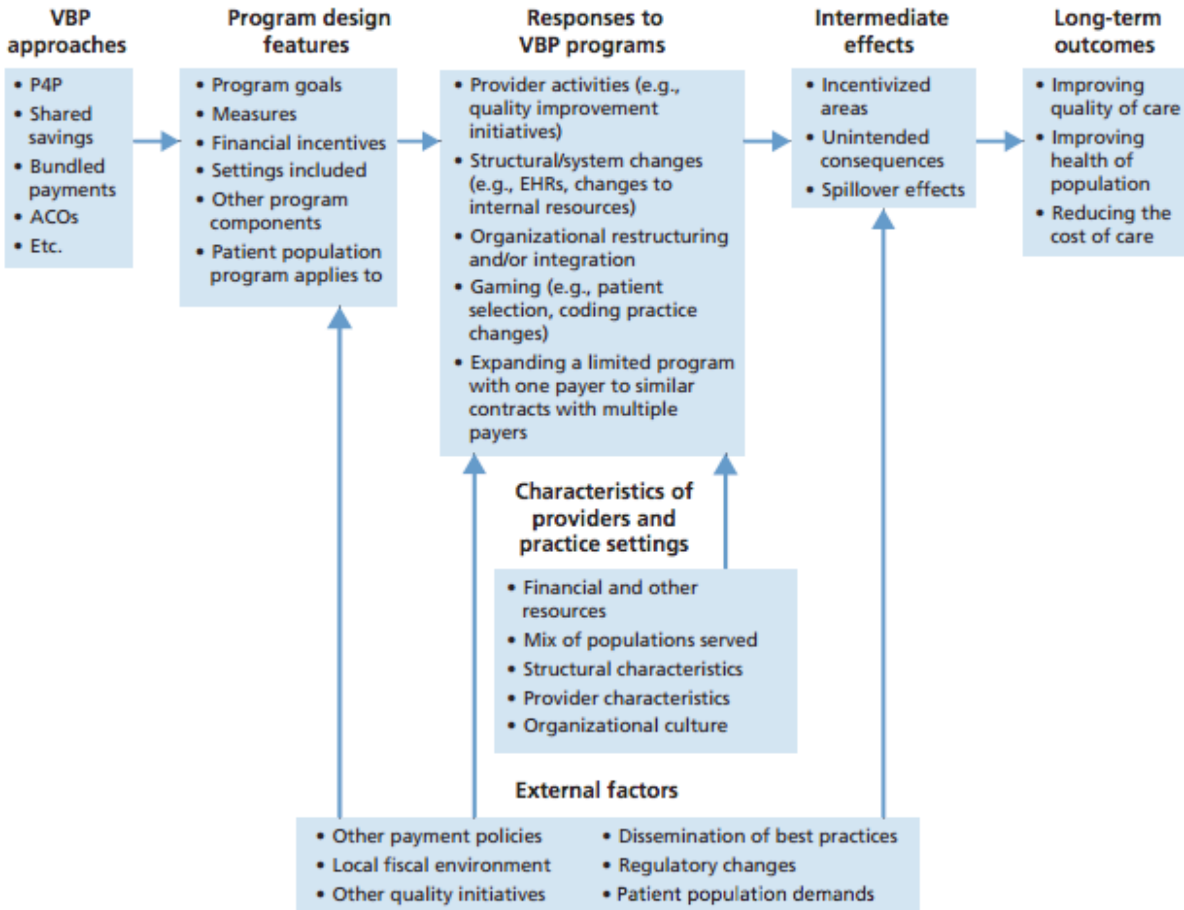
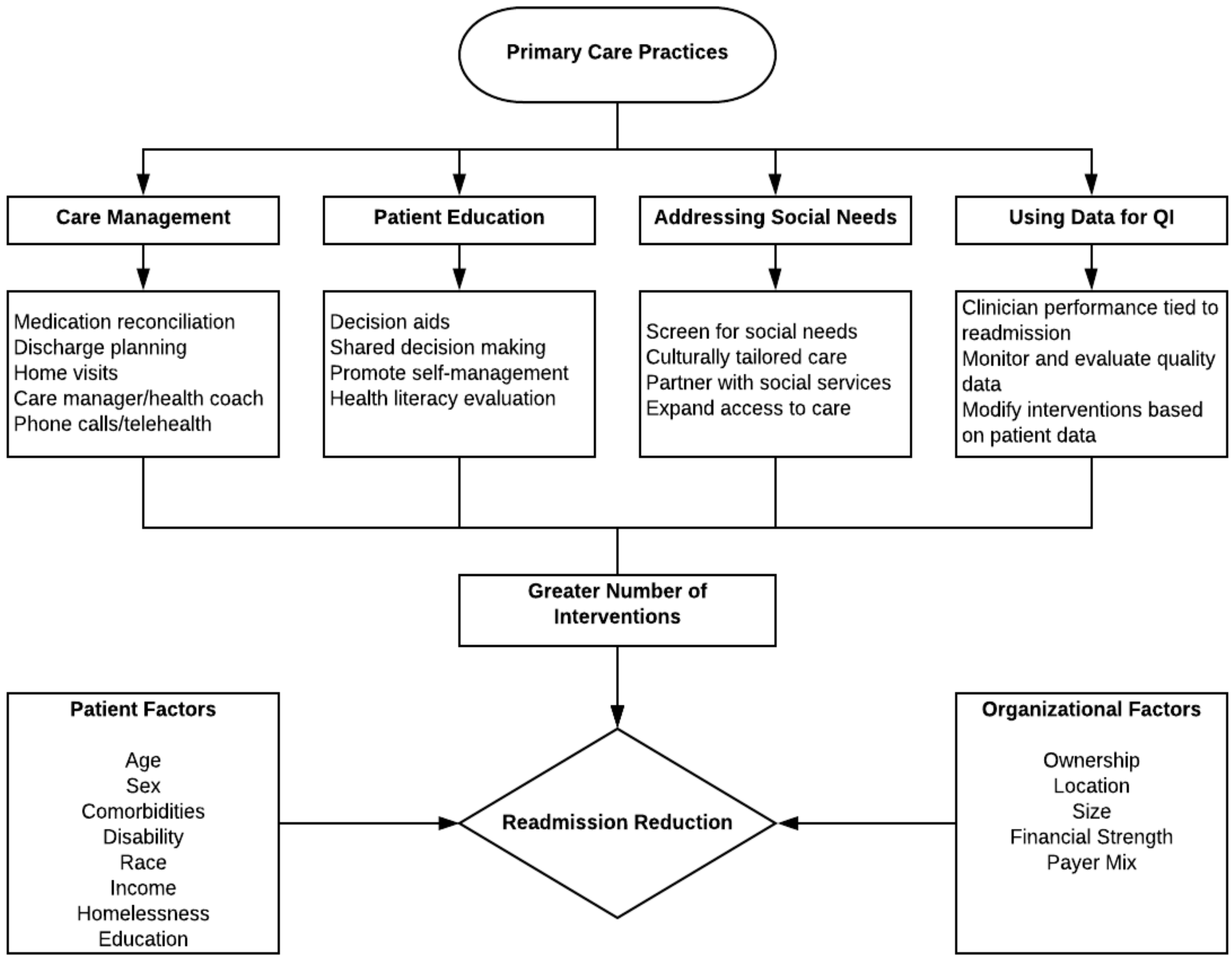


Figure 2. Conceptual Model for Aim 3



CHAPTER 2. THE ROLE OF INCENTIVE SIZE WHEN PAYING FOR PERFORMANCE: THE HOSPITAL READMISSIONS REDUCTION PROGRAM

Overview

Background: The Hospital Readmissions Reduction Program (HRRP) cuts hospitals' Medicare payments by up to three percent for high numbers of excess readmissions. As hospitals become more dependent on Medicare revenue their financial incentives to lower excess readmissions (ERRs) increase because the HRRP only targets Medicare payments.

Objective: To examine the relationship between hospitals' maximum potential HRRP payment penalty per admission and their acute myocardial infarction (AMI), heart failure (HF) and pneumonia (PN) ERRs.

Methods: We used data from Hospital Compare and CMS's annual impact files to create balanced panels of hospital-level, condition-based cohorts from 2013-2018: our final sample included 1,486 hospitals for AMI, 2,500 for HF, and 2,504 for PN. We estimated fixed effects models to examine the relationship between hospitals' maximum potential HRRP payment penalty per admission and their ERRs.

Results: Hospitals in the highest quintile of maximum potential HRRP payment penalty per admission had fewer index admissions, were smaller, and were less likely to be urban, teaching, or a disproportionate share hospital than hospitals in the lowest quintile. We found no significant association between hospitals' maximum potential HRRP payment penalty per admission and their ERRs.

Conclusion: The relatively small penalties associated with the HRRP may have acted as a trigger event, encouraging all hospitals to reduce ERRs without incentivizing differential effects based on potential penalty size. A leveling off of ERRs in recent years suggests that CMS may need to modify the HRRP moving forward.

Introduction

Pay-for-performance (P4P) is an increasingly common method for reimbursing medical providers. Policymakers have sought to leverage the use of financial rewards and penalties to influence provider behavior and achieve desired outcomes.[55,56] The hope is, according to former Health and Human Services Secretary Sylvia Burwell, that "highly motivated and rewarded" providers will improve their quality of care and performance on metrics specified by payers.[57] Furthermore, P4P has been advertised as a method for generating cost savings by motivating "higher-value care" among providers.[58]

The rationale for P4P is straightforward: if we offer providers financial incentives to deliver better care, they will do so. Yet in practice P4P has often, though not always, produced disappointing results. One large systematic review of P4P in health care concluded that, "the evidence seems insufficient to recommend widespread implementation of P4P".[47] Another large multi-country review found, "low-strength, contradictory evidence" for P4P's impact on processes of care and "no clear evidence" on its impact on patient outcomes.[59] In the US, several of Medicare's large P4P demonstrations failed to produce consistent quality improvements or significantly lower costs.[55,60–62] Private P4P initiatives have had similar results.[59,63] However, other programs, such as Medicare's Hospital Readmissions Reduction Program (HRRP), have been touted as P4P success stories.[9,20]

The lack of consistent findings supporting P4P raises a crucial question: how do providers respond to financial incentives? The answer is unclear, with no apparent correlation between the size of the incentive and the success of the P4P program.[59]

Moreover, studies that have examined the impact of incentive size on performance have typically done so at the macro level (e.g., did the program improve processes or outcomes overall).[64,65] Fewer studies have investigated how performance is impacted by incentive size within a program. This is in part because P4P initiatives commonly rely on a uniform incentive amount for all providers, making it impossible to analyze within-program effects. In contrast, Medicare's more recent value-based purchasing initiatives often include payment adjustments that operate on a sliding scale. This allows researchers to investigate the dose response relationship between incentive size and performance in these programs. Moreover, as these programs are mandatory there is less concern about selection bias compared with voluntary P4P programs.

One of Medicare's programs that allows us to investigate the dose response relationship between incentive size and performance is the HRRP. Adopted in 2010 and implemented in 2012 for acute myocardial infarction (AMI), heart failure (HF) and pneumonia (PN), the HRRP targets over 3,500 U.S. hospitals by reducing their Medicare base operating payments by up to three percent for excess AMI, HF, and PN readmissions.[3] Medicare determines the amount of excess readmissions for each hospital by calculating an excess readmission ratio (ERR) which is the number of predicted readmissions over the number of expected readmissions. A value below one means a hospital had lower than expected numbers of readmissions while values above one indicates increasing numbers of excess readmissions. Even if a hospital has zero excess readmissions for non-penalized conditions, like asthma, it can still see a decrease in Medicare reimbursement of up to three percent if its ERR is above one for any of the HRRP measures. Thus, hospitals are incentivized by the HRRP to target readmission efforts more towards penalized conditions.

Along with targeting select conditions, the HRRP reduces federal Medicare payments. Therefore, hospitals more dependent on Medicare revenue face greater financial incentive to prevent excess readmissions. A three percent reduction in Medicare payments for a hospital that sees few Medicare patients as an overall share of its admissions is a relatively smaller penalty than for a hospital more reliant on Medicare. Thus, the structure of the HRRP penalty formula allows us to compare ERRs based on the amount of revenue at risk of being penalized.

Although several studies of the HRRP have indirectly examined this topic by controlling for hospitals' percentage of Medicare patients in their readmission models,[14,36,66,67] none has directly investigated how the size of hospitals' potential HRRP penalty impacts ERRs. Furthermore, some studies have examined readmission rates longitudinally,[10,12–14,17,18] but to our knowledge none has used multiple years of panel data to control for unobserved confounders. In order to address the question of how penalty size impacts ERRs, we used 2013-2018 CMS data to examine the relationship between hospitals' maximum potential HRRP payment penalty per admission and their ERRs for AMI, HF and PN. We hypothesize that hospitals' maximum potential payment penalty per admission is negatively correlated with their ERR, holding all other factors constant.

Study Data and Methods

Data

We used data from two sources to construct our hospital-level analysis file. The first was CMS's annual impact files from fiscal years 2013-2018. These annual files are available online on the CMS website.[68] The impact files contain hospital-level data for over 3,300 hospitals on core-based statistical area designation, teaching status, number of beds, disproportionate share (DSH) percentage, Medicare days, and HRRP payment penalty, among other variables. The second source was the Hospital Compare website which includes 2013-2018 readmission data for all subsection(d) hospitals*. These files contain such variables as hospitals' ERRs, the number of index admissions and readmissions for each HRRP condition.

Patient Cohorts

After linking these two datasets using hospitals' CMS provider number, we created three different cohorts by condition: AMI, HF, and PN. We included hospitals' patients in the cohorts if they were continuously enrolled in Medicare parts A and B, aged 65 or older, and discharged alive (not against medical advice), as defined by CMS.[69] To obtain a balanced panel for each of these cohorts, we excluded hospitals if they were missing readmission data or other important characteristics for any of the six years. After the exclusions, our final sample included 1,486 hospitals for AMI, 2,500 for

*Subsection (d) hospital are general, acute care, short-term hospitals and represent the vast majority of all hospitals in the US. Those hospitals that are not included as subsection (d) hospitals included Maryland hospitals, Veteran's hospitals, critical access hospitals, cancer hospitals, children's hospitals, and inpatient psychiatry hospitals.

HF, and 2,504 for PN. Our sample for AMI was smaller as fewer hospitals had the required 25 index admissions necessary to be included in the HRRP for AMI.

Outcome

Our dependent variable was hospitals' ERR. CMS calculates ERRs by dividing a hospital's predicted readmission rate over its expected readmission rate. The predicted readmission rate is based on the hospital's patient characteristics (age and comorbidities) and their hospital intercept (e.g. the hospital's performance on readmissions after accounting for its case mix). The expected readmission rate is based on the hospital's patient characteristics and the overall mean hospital intercept.[69] A readmission must occur within 30 days of an index admission in order to be counted as a readmission. Multiple readmissions within the 30-day window do not count more than once as the outcome is dichotomous. The ERR excludes a small subset of planned readmissions like maintenance chemotherapy. We recognized the possibility that ERRs can be potentially gamed through excess coding of secondary diagnoses.[22] This is because the ERR formula presents hospitals with an opportunity to inflate their predicted readmission rate by listing a greater number of secondary diagnoses (up to 25). We therefore conducted sensitivity analyses using raw readmission rates as the outcome while adjusting for patients' hierarchical condition category score as an independent variable. The results of this model were nearly identical to the model using ERRs. Thus, we preferred to use CMS's official model for purposes of consistency with the HRRP.

Independent Variable

Our independent variable of interest was hospitals' maximum potential HRRP payment penalty per admission. In order to arrive at this variable, we first calculated each hospital's total Medicare revenue that was subject to HRRP penalties. The HRRP's three percent penalty is only applied to the base operating payment amount, which is a flat rate for all hospitals, updated on a yearly basis. We multiplied the base rate amount (published each year in CMS's final rules) by each hospital's number of Medicare admissions for the year to arrive at a hospital's total base operating revenue amount. We then multiplied this amount by three percent, the maximum HRRP penalty, to identify the largest potential amount a hospital could lose each year. Finally, we divided this figure by the total number of all admissions, not just Medicare, to obtain each hospital's maximum revenue at risk per inpatient admission.

Control Variables

To control for hospitals caring for more disadvantaged patients, we used the DSH variable in the impact file, which is the percent of a hospital's patients that meet DSH status. To account for hospital size, we included a continuous variable for the total number of beds. We did not include any time-invariant predictors in our model (e.g., teaching status or profit status) as these are controlled for by the fixed effects.

Statistical Analysis

We first split hospitals into quintiles based on their average maximum HRRP penalty per admission for AMI, HF, and PN between fiscal years 2013-2018. We then compared mean observed (non-risk adjusted) readmission rates for each quintile over time. Next, we restricted our sample to only hospitals in the lowest and highest quintiles of maximum HRRP penalty per admission for AMI, HF, and PN. We then compared the results for the two groups using t-tests for normally distributed continuous variables, Mann Whitney U tests for non-normally distributed continuous variables, and chi^2 tests for binary and categorical variables.

We then constructed fixed effects models for all hospitals in our sample, using ordinary least squares regression in order to examine the impact of a hospital's potential maximum HRRP penalty per admission on its AMI, HF, and PN ERRs between fiscal years 2013-2018. We tested for the use of pooled regression and random effects using Breusch-Pagan and Hausman tests. The results of these tests supported the use of a fixed effects model over the other two models. We accounted for potential secular time trends by introducing a dummy variable for each year.

Finally, as a sensitivity analysis, we estimated a linear regression model using 2018 data and changes in ERR from 2013-2018 as the dependent variable. The goal of this model was to examine if hospitals with greater potential maximum HRRP penalties per admission demonstrated more improvement in ERR over time. Since this was a cross-sectional model we added additional time-invariant covariates that we did not include in our fixed effects model. We included variables for hospital teaching status, urban/rural location, and region. We clustered all standard errors at the hospital level. All analyses were conducted with Stata software, version 15.1.

Results

Hospitals in all five quintiles of maximum HRRP penalty per admission experienced clinically significant declines in observed readmission rates for AMI, HF, and PN between 2013-2016 (Figure 1). However, these declines appear to have slowed down beginning in 2017. Overall, the greatest declines in observed readmission rates were for AMI (2.8%) and HF (2.6%), with PN displaying more modest reductions (1.5%). The trends in observed readmission rates were similar across quintiles of maximum HRRP penalty per admission. Compared to hospitals in the lowest quintile of maximum HRRP penalty per admission, readmission rates for hospitals in the highest quintile did drop more but this relationship was not significant for any of the three conditions (AMI: -2.9% vs. -2.8%; HF: -2.9% vs. -2.4%; PN: -1.7% vs. -1.3%).

We observed several significant differences between hospitals in the lowest and highest quintiles of maximum HRRP penalty per admission (Table 1). Hospitals in the highest quintile had significantly fewer total admissions (AMI: 3,930 vs. 4,386; HF: 2,199 vs. 3,202; PN: 2,082 vs. 3,345) but significantly more Medicare admissions (AMI: 2,476 vs. 1,277; HF: 1,220 vs. 779; PN: 1,161 vs. 836). Hospitals in the highest quintile received significantly higher average HRRP penalties (AMI: 0.53% vs. 0.31%; HF: 0.51% vs. 0.28%; PN: 0.52% vs. 0.30%) but, on average, hospitals in both groups were penalized some amount a similar number of years (five). On average, hospitals in the highest quintile of maximum HRRP penalty per admission had significantly lower proportions of DSH patients (AMI: 19% vs 39%; HF: 21% vs. 37%; PN: 21% vs. 38%), fewer beds (AMI: 179 vs. 398; HF: 106 vs. 302; PN: 101 vs. 310), and lower casemix scores (AMI: 1.55 vs. 1.77; HF: 1.42 vs. 1.68; PN: 1.40 vs. 1.69). Hospitals in the highest quintile were significantly less likely to be teaching hospitals (AMI: 26% vs 70%; HF: 15% vs. 58%; PN: 14% vs. 57%), large urban (AMI: 28% vs 69%; HF: 21% vs. 69%; PN: 21% vs. 68%), or located in the West (AMI: 6% vs 35%; HF: 5% vs. 36%; PN: 5% vs. 36%). We did not witness significant differences in observed readmission rates or ERRs for any of the conditions.

We subsequently used fixed effects to model hospitals' ERRs as a function of their maximum potential HRRP penalty per admission, DSH percentage, and number of beds (Table 2). A one dollar increase in hospitals' maximum potential HRRP penalty per admission was associated with a 0.0002 increase in their AMI and PN ERRs and a 0.0001 increase in their HF ERR. This relationship was not statistically significant for any of the three conditions. We did not observe a statistically significant relationship between hospitals' DSH percentage or number of beds and their ERR.

Sensitivity Analyses

There was an inconsistent relationship between maximum potential HRRP penalty per admission and changes in hospitals' ERR from 2013 to 2018. For AMI, the relationship was negative and statistically significant. As hospitals' maximum potential HRRP penalty per admission increased their ERR decreased over time. We observed a reduction in ERR of 0.0005 points for each additional dollar in maximum potential HRRP penalty per admission. We did not detect a statistically significant relationship between these variables for either HF or PN.

Discussion

The HRRP has been championed by many health policymakers and analysts as a successful example of P4P, credited with reducing readmission rates. Readmission rates declined substantially over the first few years of the HRRP and have since begun to level off, a finding that we witnessed as well when examining observed readmission rates.[10,70] Improved performance on readmissions does not appear to be driven by the size of the HRRP's payment penalties. Our study found that the prospect of larger penalties was not consistently associated with lower ERRs. Although we did observe a significant association between hospitals' maximum potential HRRP penalty per admission and improvement in ERR for AMI from 2013 to 2018, this was not true for HF or PN.

Perhaps the most plausible explanation for this null finding is that HRRP penalties are too small to result in differential performance on excess readmissions. While some hospitals face the potential of millions of dollars in lost revenue if they are penalized the maximum three percent, the vast majority of hospitals are penalized less than one percent. In 2017, the average payment penalty was just over $200,000.[70] Some researchers have concluded that financial incentives must be large, up to 15%, in order to spur improvement but this does not seem to be supported by experiences with the HRRP.[65] Instead, the modest penalties associated with the HRRP may have acted as a trigger event, encouraging all hospitals to reduce ERRs without incentivizing differential effects based on potential penalty size. It could be that the HRRP has sparked a cultural shift for all hospitals, with readmission reduction efforts signaling high-quality care. This shift may not have occurred if financial incentives, no matter how small, were absent. A recent survey of nearly 1,000 hospitals found that almost two-thirds of executives cited the HRRP as having a “significant” impact on their readmission reduction efforts.[71]

From CMS’s perspective, the HRRP penalties appear to have had their desired effect of reducing excess readmissions,[10,12,13,72] while also saving Medicare over $2 billion since the program’s inception.[70] However, some researchers dispute these findings, arguing that the success of the HRRP is a function of coding changes or regression to the mean and not the HRRP itself.[21,22] Others contend that the program has led to increases in mortality rates.[25] While these are serious concerns, the literature is divided on these claims.[27] As with many P4P programs, unintended consequences can be just as important as the impact of the program itself. Our study did not investigate these topics but as the HRRP moves forward CMS must carefully monitor these issues.

Moreover, declines in readmission rates have levelled off since 2016. This could be due to the fact that the easy gains in reducing excess readmissions have already been made. It could also be caused by regression to the mean, with declines in readmission rates mostly attributed to improvements in hospitals with the highest baseline rates.[21] While the HRRP’s penalties may have been large enough to create a culture of readmission reduction, they may not be large enough to incentivize hospitals to invest the additional resources necessary to achieve further reductions in excess readmissions. If CMS believes this to be the case, then federal policymakers may want to examine the possibility of implementing larger payment penalties.

However, if excess readmissions are no longer being reduced because there is little room for additional improvement, then increasing the penalty size will not be an effective strategy. CMS has made it clear that the goal of the HRRP is not to "drive hospitals to a zero readmission rate."[73] If hospitals are in fact reaching a point of diminishing marginal returns, then the HRRP may not be able to shift the readmissions curve much further to the left. However, CMS can still leverage the program to shrink the distribution of the curve. One approach could be to reserve some of the HRRP penalties and allocate them to training/educational materials for hospitals with consistently high numbers of excess readmissions through programs like the Partnership for Patients. We have evidence on the types of activities and interventions associated with lower excess readmissions and it may be that consistently poor preforming hospitals could improve their performance by implementing these strategies more regularly.[44,45]

Limitations

One limitation of our study is that we used retrospective data, thus our study may not properly control for unobserved confounders. We attempted to mitigate this limitation by using a fixed effects model. Fixed effects can control for unobserved characteristics like hospital revenue sources but only if they do not change significantly over the study period. Therefore, if hospitals, or certain subsets of hospitals, have experienced impactful changes in their inpatient/outpatient revenue share, our model may not properly control for these types of factors. Another limitation of our study is that we did not have access to hospitals' all-payer revenue data. We attempted to account for hospitals’ reliance on Medicare revenue through the use of a maximum potential HRRP penalty per admission variable. However, it may have been more appropriate to calculate hospitals’ revenue at risk as a proportion of their Medicare revenue over their total revenue, something we were unable to do. Lastly, while payer mix is an important variable in terms of the amount of revenue at risk for hospitals under the HRRP, it is something hospitals have little control over. Consequently, it may be that hospitals are unable to significantly alter their proportion of Medicare revenue in order to face smaller penalties.

Conclusion

We found that the size of hospitals’ potential payment penalty under the HRRP was not associated with their ERR. In practice, this finding suggests that hospital performance in the HRRP is not being dictated by the size of the incentive. However, given the initial success of the HRRP in reducing excess readmissions, we cannot discount the role of incentives as a triggering mechanism that encouraged all hospitals to perform better. Concerns about possible gaming and the impact of the HRRP on mortality rates suggests that CMS may need to closely monitor the HRRP moving forward. Additionally, recent slowdowns in the readmission reduction trend may necessitate new policies or strategies in order to further reduce readmission rates.

Table 1. Hospital Characteristics by Lowest and Highest Quintile of Maximum HRRP Penalty Per Admission, FY 2013-2018

	AMI		HF		PN	
	Lowest Quintile	Highest Quintile	Lowest Quintile	Highest Quintile	Lowest Quintile	Highest Quintile
N	297	295	500	500	501	500
Maximum Penalty Per Admission per year ($), mean (SD)	40.49 (6.56)	88.86 (6.75)***	39.69 (8.51)	91.86 (7.77)***	40.69 (8.09)	92.65 (8.26)***
Excess Readmission Ratio per year, mean % (SD)	1.01 (0.06)	1.01 (0.06)	1.00 (0.07)	1.01 (0.07)	1.00 (0.06)	1.01 (0.07)
Observed Readmission Rate per year, mean % (SD)	17.91 (3.83)	18.49 (4.45)	22.74 (4.02)	22.89 (3.61)	17.68 (3.30)	17.48 (3.04)
Number of admissions per year, median (IQR)	4385.50 (3107.00, 6507.67)	3930.17 (2682.17, 5564.17)**	3201.92 (1694.08, 5333.42)	2199.08 (1131.08, 3741.50)***	3344.50 (1792.17, 5616.00)	2082.33 (952.75, 3673.58)***
Number of Medicare admissions per year, median (IQR)	1277.33 (891.45, 1843.52)	2475.93 (1725.49, 3417.10)***	779.27 (369.76, 1327.14)	1219.62 (639.27, 2081.98)***	836.23 (399.26, 1417.26)	1161.18 (556.78, 2039.38)***
Readmission penalty % per year, median (IQR)	0.31 (0.16, 0.52)	0.53 (0.25, 0.96)***	0.28 (0.12, 0.51)	0.51 (0.25, 0.93)***	0.30 (0.13, 0.52)	0.52 (0.26, 0.95)***
Number of years penalized, mean (SD)	5.08 (1.48)	5.03 (1.52)	5.05 (1.48)	5.04 (1.46)	5.04 (1.50)	5.06 (1.40)
DSH % per year, median % (IQR)	38.67 (28.72, 49.12)	19.22 (12.91, 25.41)***	37.67 (27.70, 52.19)	21.33 (15.12, 27.27)***	37.37 (27.50, 50.57)	21.29 (15.20, 26.79)***
Number of beds per year, median (IQR)	397.67 (274.50, 534.67)	179.00 (121.00, 248.00)***	301.92 (170.00, 458.42)	106.17 (64.08, 180.83)***	310.33 (169.83, 466.50)	100.75 (58.00, 174.17)***
Casemix per year, median (IQR)	1.77 (1.63, 1.94)	1.55 (1.45, 1.68)***	1.68 (1.53, 1.85)	1.42 (1.26, 1.56)***	1.69 (1.53, 1.85)	1.40 (1.23, 1.54)***
Teaching, N (%)	207 (69.7%)	76 (25.8%)***	290 (58.0%)	76 (15.2%)***	285 (56.9%)	72 (14.4%)***
Urban/Rural, N (%)		***		***		***
Large Urban	205 (69.0%)	83 (28.1%)	343 (68.6%)	106 (21.2%)	339 (67.7%)	104 (20.8%)
Urban	89 (30.0%)	126 (42.7%)	140 (28.0%)	148 (29.6%)	139 (27.7%)	137 (27.4%)
Rural	3 (1.0%)	86 (29.2%)	17 (3.4%)	246 (49.2%)	23 (4.6%)	259 (51.8%)
Region, N (%)		***		***		***

Northeast	56 (18.9%)	63 (21.4%)	94 (18.8%)	93 (18.6%)	95 (19.0%)	90 (18.0%)
Midwest	73 (24.6%)	133 (45.1%)	121 (24.2%)	203 (40.6%)	118 (23.6%)	196 (39.2%)
South	63 (21.2%)	80 (27.1%)	107 (21.4%)	180 (36.0%)	107 (21.4%)	189 (37.8%)
West	105 (35.4%)	19 (6.4%)	178 (35.6%)	24 (4.8%)	181 (36.1%)	25 (5.0%)

Source: Authors' analysis of data from FY 2013-2018 CMS annual impact files and Hospital Compare data. **Notes**: We split hospitals into quintiles based on their mean maximum HRRP penalty per admission. We conducted comparisons of continuous variables using non-parametric tests for right-skewed variables and t tests for normally distributed variables. We used chi-squared tests to compare binary and categorical variables. *p<0.05 **p<0.01 ***p<0.001.

Table 2. Fixed Effects Regression Model Results for Excess Readmission Ratios for AMI, HF, PN, FY 2013-2018

	AMI			HF			PN		
	Coef.	SE	P Val	Coef.	SE	P Val	Coef.	SE	P Val
Max HRRP penalty per admit ($)	0.0002	0.0002	0.196	0.0001	0.0001	0.138	0.0002	0.0001	0.061
DSH %	-0.0002	0.0003	0.535	0.0001	0.0002	0.514	0.00001	0.00002	0.963
Number of beds	0.00003	0.00004	0.466	0.00005	0.00003	0.099	0.00005	0.00003	0.086
Year (2013 reference)									
2014	0.002	0.002	0.194	0.002	0.001	0.091	0.001	0.001	0.254
2015	0.004	0.002	0.051	0.002	0.001	0.108	0.002	0.001	0.115
2016	0.007	0.003	0.008	0.004	0.002	0.023	0.004	0.002	0.117
2017	0.008	0.003	0.006	0.005	0.002	0.014	0.005	0.002	0.014
2018	0.007	0.003	0.022	0.005	0.002	0.008	0.005	0.002	0.024

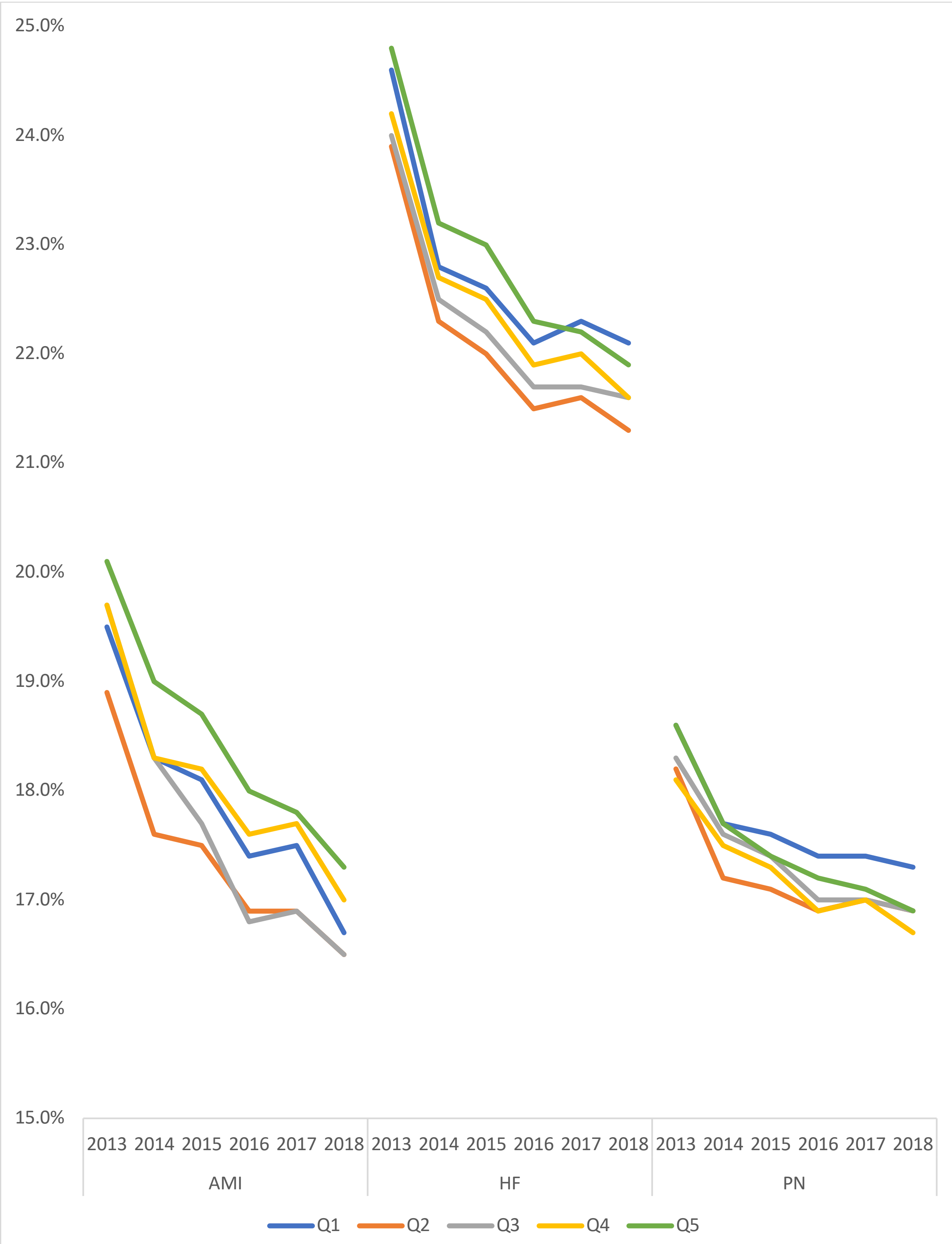
Source: Authors' analysis of data from FY 2013-2018 CMS annual impact files and Hospital Compare data. **Notes**: We used fixed effects ordinary least squares regression with standard errors clustered at the hospital level.

Table 3. OLS Model Results for Differences in Excess Readmission Ratios between 2013-2018 for AMI, HF, PN, FY

	AMI			HF			PN		
	Coef.	SE	P Val	Coef.	SE	P Val	Coef.	SE	P Val
Max HRRP penalty per admit ($)	-0.0005	0.00018	0.011	-0.00018	0.00012	0.131	0.00005	0.00012	0.697
DSH %	-0.0009	0.00020	<0.001	0.00006	0.00013	0.647	0.00029	0.00013	0.031
Number of beds	-0.00002	0.00001	0.273	-0.00002	0.00001	0.066	0.000003	0.00001	0.775
Teaching	-0.0059	0.00563	0.296	0.00518	0.00426	0.224	-0.00307	0.00450	0.495
Large Urban									
Urban	0.02182	0.00583	<0.001	0.01239	0.00428	0.004	0.00485	0.00445	0.275
Rural	0.02419	0.00696	0.001	0.00416	0.00492	0.398	-0.00387	0.00508	0.446
Northeast									
Midwest	0.02809	0.00727	<0.001	0.01983	0.00558	<0.001	-0.00597	0.00557	0.284
South	0.02381	0.00765	0.002	0.01073	0.00577	0.063	-0.00707	0.00569	0.215
West	0.03895	0.00862	<0.001	0.01687	0.00644	0.009	0.00123	0.00660	0.852

Source: Authors' analysis of data from FY 2013-2018 CMS annual impact files and Hospital Compare data. **Notes**: We used ordinary least squares regression with standard errors clustered at the hospital level.

Figure 3. Observed AMI, HF, and PN Readmission Rates by Quintile of Max Potential HRRP Penalty per Admission FY 2013-2018



Source: Authors' analysis of data from FY 2013-2018 CMS annual impact files and Hospital Compare data. **Notes**: We split hospitals into quintiles based on their maximum potential HRRP penalty per admission.

CHAPTER 3. THE IMPACT OF THE HOSPITAL READMISSIONS REDUCTION PROGRAM ON MEDICARE ADVANTAGE PATIENTS: A RETROSPECTIVE STUDY OF THREE LARGE STATES

Overview

Background: The Hospital Readmissions Reduction Program (HRRP) has been credited with reducing readmissions for Traditional Medicare (TM) but less is known about the program's impact on Medicare Advantage (MA).

Objective: Determine whether the HRRP reduced MA readmission rates.

Methods: We compared readmission rates for three groups: targeted conditions for TM and MA and non-targeted conditions for TM, using MA admissions for non-targeted conditions as our control. We constructed triple differences linear probability models examining changes in unplanned readmission rates before and after the HRRP.

Results: Post-HRRP readmission rates dropped by the same amount for TM and MA for AMI (1.0 percentage points) and HF (0.5 percentage points). There was no statistically significant change in TM or MA pneumonia readmission rates or TM readmission rates for non-targeted conditions.

Conclusion: We found significant evidence of HRRP spillover for MA patients. The size of this spillover depends, in part, on assumptions about unobserved MA policies or interventions.

Introduction

Congress enacted the Hospital Readmissions Reduction Program (HRRP) with the goal of reducing readmission rates for Medicare patients. The HRRP was one of several payment reforms created by the Affordable Care Act to improve quality and reduce Medicare spending growth. The HRRP reduces hospitals' Medicare payments by up to three percent for higher-than-expected readmission rates for Traditional Medicare (TM) patients admitted for select conditions. Over time, the Centers for Medicare and Medicaid Services (CMS) has expanded the list of conditions from the original three, acute myocardial infarction (AMI), heart failure (HF), and pneumonia (PN), to a total of six. Much of the research to date has focused on the effect of the HRRP on TM beneficiaries but less is known about its effects on Medicare Advantage (MA) patients.

Under MA, Medicare contracts with an insurer that receives a fixed amount of money for each enrollee. MA's capitated reimbursement structure incentivizes health plans to reduce excess hospitals readmissions. Medicare beneficiaries are attracted to MA largely because of the enhanced benefits that most plans offer.[74] MA enrollment has grown substantially over the past decade from 10.5 million persons in 2009 to 22 million in 2019.[51] Given that growth, it is crucial to understand how hospital readmission policies are impacting MA patients. Yet there are only a limited number of HRRP studies focused on MA patients. That may reflect the fact that two of the most common data sources for readmission analyses (Medicare claims data and the National Readmission Database) do not include data for MA patients.

One major question in particular is whether MA patients have experienced reductions in readmission rates since the HRRP's implementation. While the HRRP only applies to admissions for TM patients, hospitals regularly admit both TM and MA patients. It may be that hospitals are reserving their readmission reduction resources for TM patients. Activities like hiring care managers for high-risk patients, conducting home visits, and allotting time to patient education are both time consuming and expensive.[45,75,76] However, if hospitals do not focus these types of activities solely on their TM patients, MA patients are also likely to be affected by the increased attention on readmission reduction.

We are aware of three studies that examined the impact of the HRRP on readmission rates for MA patients.[19,77,78] Two of these studies, one focusing on California and another on Florida, found statistically significant spillover effects for MA patients. In the California study, both TM and MA patients experienced significant declines in readmission rates after implementation of the HRRP, although the effect was stronger for TM patients.[19] In the Florida study, MA patients actually experienced a larger decline in readmission rates than TM patients.[77] The third study used national data from 2011-2014 and concluded that the HRRP did not lead to significant reductions in readmission rates for MA patients.[78]

Our approach differs from these studies in terms of our model and data. Most notably, we designated MA admissions for non-targeted conditions (NTCs) as our control group. Identifying true control groups is challenging when evaluating federal policies since there is the possibility that the entire population is impacted in some way. We decided on MA NTC admissions as our control group since these admissions are neither part of a payer or condition targeted by the HRRP. We prefer this approach, which is also advocated by MedPAC[79], as opposed to using admissions for MA patients in non-penalized hospitals as our control group.[17,77] This is because hospitals' penalty status is not static and hospitals that are not penalized are still incentivized to reduce readmission rates to prevent future penalties.

We analyzed inpatient hospitalization data from three large states with high rates of MA penetration, California, Florida, and New York, in order to assess potential spillover effects of the HRRP for MA patients. We compared readmission rates between 2007-2014 for three groups: 1) TM admissions for AMI, HF, and PN; 2) MA admissions for AMI, HF, and PN; and 3) TM admissions for NTCs, using MA admissions for NTCs as our control group. We determined spillover to be present if we witnessed significant post-HRRP declines in MA readmission rates for AMI, HF, or PN or TM readmission rates for NTCs, compared with changes in readmission rates in our control group.

Study Data and Methods

Data

We relied on four data sources. The first was the Healthcare Cost and Utilization Project's State Inpatient Databases (SID) for California (2007-2011), Florida (2007-2014), and New York (2007-2014). These data are owned by the Agency for Healthcare Research and Quality and include 100% of short-stay, acute-care inpatient hospitalizations.[80] Each state decides whether to participate in the SID. The SID include unique patient and hospital identifiers that can be linked across time to track admissions and readmissions for each patient. The SID also include patients' diagnoses, disposition status, comorbidities, payer, and demographic information.

In 2011, California stopped participating in the SID. However, the state continued to grant access to later years of data to researchers. The Patient Discharge Database can be purchased directly from California and includes all the data that California would have provided to the SID for 2012-2014. Much like the SID data, the Patient Discharge Database includes 100% of short-stay acute care inpatient hospitalizations, unique patient and hospital identifiers, and other key variables detailed in the paragraph above.[81]

Our final two datasets were the 2012-2014 Urban Influence Codes as determined by the Department of Agriculture and the 2012-2014 American Community Survey owned by the Census Bureau. We used variables from these datasets to adjust for patient location and median patient income for the Patient Discharge Database, as these are present in the SID. The Patient Discharge Database includes patient zip codes, allowing us to link patients to these two data sources.

Sample

We combined admissions for California, Florida, and New York patients into a single cohort. We used ICD-9 codes from the primary discharge diagnosis to identify AMI, HF, PN and NTC admissions (N=16,421,284). For AMI, HF, and PN, we used the same ICD-9 codes as used by the HRRP (Appendix Table A1). For NTCs, we excluded all admissions with primary diagnoses of AMI, HF, and PN as well as hip/knee replacement or chronic obstructive pulmonary disorder, conditions that were added to the HRRP during the final years of the study period.

We then used the approach developed by Yale and CMS to create our study sample.[82] We included index admissions for Medicare patients 65 years or older admitted to a short-term, acute-care inpatient hospital. If a patient had one or more admissions within 30 days of a previous admission we only included the first admission as an index admission. We identified admissions as either TM or MA based on the primary payer. We then excluded index admissions for patients who died before discharge, were discharged against medical advice, did not have at least 30 days of follow up data, or switched between TM and MA within 30 days of an index admission. For California, we also excluded index admissions occurring in the final month of 2011 as these patients could not be tracked in the California Patient Discharge Database. Finally, we combined all transfers into one continuous hospitalization with the discharge date from the receiving hospital indicating the start of the follow up period. Our final cohort included 10,171,499 TM admissions and 4,324,233 MA admissions, from 6,660,274 patients in 800 hospitals.

Outcome

Our outcome for this study was unplanned 30-day readmissions. We employed CMS's planned readmission algorithm 3.0 to determine whether or not a readmission was planned.[82] We defined readmission as a binary variable indicating the presence of a readmission within 30 days of an index admission. Thus, for each condition no index admission could have more than one readmission. Moreover, a readmission could not serve as an index admission for the same condition. However, like the CMS measures, a readmission could be an index admission for another condition. For example, if a patient had an index admission for AMI and was subsequently readmitted within 30 days for HF, that admission counted as a readmission for AMI and an index admission for HF.

Statistical Analyses

We first compared baseline characteristics of TM and MA admissions using Pearson's chi-square tests for binary variables, Fisher's exact test for categorical variables, t-tests for normally distributed continuous variables, and Mann-Whitney U tests for non-normally distributed continuous variables.

Next, we constructed triple differences linear probability models to examine AMI, HF, and PN readmission rates for TM and MA admissions before and after implementation of the HRRP (2007-2011 vs. 2012-2014). As opposed to traditional difference-in-differences models, triple differences allows us to more robustly control for confounding factors while including multiple comparison groups, enabling the detection of spillovers.[83] We compared readmission rates for three groups of admissions, TM admissions for AMI, HF, or PN, TM admissions for NTCs, and MA admissions for AMI, HF, or PN with our control group, MA admissions for NTCs.

We included covariates in our models for patient age, sex, race, urban/rural location, median county-level income, and whether the admission occurred during the weekend. We also included the number of secondary patient comorbidities listed during the index admission (continuous) in the vector of patient-level characteristics. Individuals could have a maximum of 14 secondary diagnoses for each index admission. We relied on the same set of diagnoses used by CMS's hospital-wide readmission measure.[84] We list all condition categories included in our risk-adjustment model in our Appendix Table A2. We also controlled for hospital and state-level fixed effects as well as yearly trends. We clustered all standard errors at the hospital level. We conducted all analyses in Stata version 15.1.

Sensitivity Analyses

We analyzed 30-day readmissions as a linear probability model. However, since we defined readmission as a binary outcome, we also tested the use of logit models for all analyses. The results of these models were nearly identical, which is not surprising as linear probability models closely estimate logit models when the probabilities are not close to 0 or 1, which is the case for the average probability of being readmitted.[85] Thus, we preferred linear probability models for ease of interpretation.[86]

We also tested the parallel trends assumption for each cohort (AMI, HF, PN, and NTCs). The parallel trends assumption states that trends between the intervention and control groups should be parallel prior to policy implementation. To test this, we limited our data to only the pre-period, 2007-2011. We reran all our models using 2007-2010 data as the pre-period and 2011 data as an artificial post-period. We did not observe significant differences in readmission rates in 2011, supporting the parallel trends assumption for our cohorts.

Limitations

There are several limitations of our study. First, it is possible that our estimates are biased due to omitted variables. We attempted to account for this factor by using a triple-differences framework. Second, triple-differences models assume no spillover to the control group in the post treatment period. However, it is not uncommon to rely on these models to examine spillover effects of policy interventions.[15,17,77] We considered an interrupted time series model with a control group instead of triple-differences; however, the smallest unit of analyses was quarterly readmission rates, leaving us with too few data points to confidently assess pre and post-HRRP trends. Third, MA patients are healthier and more likely to leave MA plans for TM as their health worsens.[87] We attempted to mitigate these differences by relying on the risk-adjustment approach employed by CMS's hospital-wide readmission measure. Yet, we could not replicate their approach exactly as we did not have access to outpatient claims data, which CMS also uses for risk adjustment. If TM patients' outpatient claims included a significantly different mix or number of comorbidities than their inpatient claims, our models may understate the reductions in risk-adjusted readmission rates for TM patients. We conducted sensitivity analyses using the Charlson[88] and Elixhauser[89] comorbidity indices and observed nearly identical results for all our models. Fourth, we were unable to control for hospital-level factors like teaching status or ownership as these data are not available in the SID or Patient Discharge Database. However, this would only bias our results if they changed over time within hospitals over the course of our study. Lastly, while California, Florida, and New York are large states with high MA penetration rates, they may not be nationally representative.

Results

Descriptive statistics (Table 4) demonstrated that compared with MA, TM patients were older (79 vs. 78), more likely to be female (57.3% vs. 55.4%), had more comorbidities (1.55 vs. 1.43), experienced longer median length of stay during hospitalization (4 vs. 3 days), were more likely to be white (74.3% vs. 65.2%), were less likely to live in large metropolitan areas (65.0% vs. 81.7%), and were more likely to be in the top quartile of median income (24.8% vs. 21.9%). We also compared baseline characteristics by condition and state in our Appendix Tables A3 and A4.

Unadjusted, unplanned readmission rates demonstrated similar trends for TM and MA admissions prior to implementation of the HRRP for both targeted and NTCs (Figure 2). Readmission rates were noticeably higher for TM admissions for all conditions during the entire study period. For AMI, unadjusted, unplanned rates showed a slightly downward trend prior to the HRRP, with the trend accelerating for both groups of admissions after 2011. The trend for HF was slightly upward prior to the HRRP, with a sharp decline after 2011 for both TM and MA. TM and MA readmission rates for both PN and NTC were steady before the HRRP and began to fall after 2011, with sharper declines witnessed in PN.

The results of our DDD models revealed statistically significant reductions in readmission rates for both TM and MA admissions for AMI and HF, relative to declines in readmission rates for MA NTC admissions (Table 5). On average, readmission rates for both TM and MA admissions for AMI dropped by 1.0 percentage points after implementation of the HRRP. For HF, the decreases were 0.5 percentage points for both TM and MA admissions. For PN, we observed a non-significant decline of 0.3

percentage points for TM admissions and no decline for MA admissions. We also witnessed a statistically significant increase of 0.2 percentage points in post-HRRP readmission rates for TM NTCs. All of these differences were much smaller than the unadjusted post-HRRP declines observed in Figure 1. This is because there was also a significant decline in readmission rates of 0.5 percentage points in our control group after the implementation of the HRRP. We conducted post-estimation analyses, which demonstrated that we would need to attribute at least half of the decline in MA admissions for NTCs to the HRRP in order to credit the HRRP with statistically significant declines in all comparison groups (Table 6). We include the full results of our regression models in Appendix Table A5.

Discussion

The HRRP led to statistically significant declines in readmission rates for both TM and MA patients admitted for AMI and HF. However, we did not observe significant declines in readmission rates for either MA or TM PN admissions. Moreover, we found a statistically significant increase in readmission rates for TM patients admitted for NTCs after implementation of the HRRP. We believe the reason for our PN and NTC results is because our control group experienced significant spillover. After implementation of the HRRP, readmission rates for MA NTC admissions declined by 0.5 percentage points. What is unclear is how much of this reduction is due to spillover from the HRRP and how much is due to some other underlying policy, intervention, or change. One of the challenges in analyzing federal policy is the ability to detect a true control group. While MA patients admitted for NTCs were not subject to the HRRP, nor were they admitted for conditions targeted by the HRRP, we cannot rule out the possibility that this group also experienced spillover. If the majority of the decline in readmissions for this group was due to the HRRP then our models would have predicted greater spillover for our comparison groups.

Our findings add to the growing body of evidence showing positive spillover effects of the HRRP for other conditions and payers.[19,35] The spillover effects may be due to several factors. First, the scope of conditions and services targeted by HRRP has expanded substantially since it was implemented in 2012. The program initially only assessed readmissions for AMI, HF, and PN. The next year, CMS announced that they would add measures for hip/knee replacement and chronic obstructive pulmonary disorder. In 2014, CMS further expanded the program by revealing that they would be adding coronary artery bypass graft surgery in 2016. Because hospitals are more likely to be penalized as more measures are added,[3] it is becoming increasingly difficult for hospital executives and clinicians to ignore the growing pressure to reduce readmissions, which may explain spillover effects to MA.

Second, it might be easier for hospitals to implement a broader readmission reduction strategy rather than target several conditions or payers. The number and types of pay-for-reporting and pay-for-performance requirements have exploded over the last decade, with the National Quality Forum currently endorsing over 250 hospital-based measures.[90] This number balloons to well over 1,000 for all measures in federal and private programs.[91] In recognition of the potential challenge, the Government Accountability Office has recommended stricter measure harmonization[92] and CMS has convened a private-public partnership tasked with creating a core set of measures.[93]

While Congress enacted the HRRP with the initial goal of reducing readmission rates for penalized conditions, the increasingly complex quality measurement environment may have made it more difficult to solely focus on HRRP-affected patients. Thus, hospitals could be employing a more global approach to readmission reduction because it is less costly and easier to implement than targeted, policy-specific readmission reduction plans.

Third, hospital executives have cited the HRRP as a key policy driving new initiatives to reduce readmission rates.[71] This has coincided with a growing literature base on the types of interventions most likely to reduce readmission rates. Interventions like Project RED,[43] the Care Transitions Intervention,[40] and systematic reviews of readmission interventions[94,95] have provided quality improvement officers and clinicians with more evidence-based strategies. This has led to increased emphasis by hospitals on introducing multi-component interventions that rely on combining strategies like improved discharge planning, medication reconciliation, and follow-up calls with patients post-discharge.[96] The emergence of this evidence base, driven in large part by the HRRP, may have helped convince hospital leadership that reducing readmissions is feasible.

Even with increased attention on reducing hospital readmissions, spillover effects do not appear to be universal. The size of the spillover in our study varied by condition, with the lowest amount witnessed in PN admissions. Although the HRRP has been credited with reducing readmission rates for hip/knee procedures,[16] such effects have not been observed for procedures like aortic aneurysm repair, colectomy, cystectomy, or, lung resection.[97,98] Thus, hospitals may need to strike a balance between hospital-wide interventions that benefit a wide array of patients, and condition-specific interventions that do not respond as well to universal readmission reduction strategies.

Our detection of spillover effects for MA patients might also depend on the data source and modeling methodology. While our main findings are consistent with other state-based studies[19,77], they contradict one national study that found higher, not lower, risk-adjusted readmission rates for MA patients between 2011-2014.[78] We believe this discrepancy is due to differences in data and methods. We used 2007-2014 data as opposed to 2011-2014 data. Our study relied on state-level data that included all Medicare inpatient hospitalizations. The national study cited above used a combination of MedPAR and HEDIS data which capture most, but not all, MA inpatient stays. Our study also differed in that we used a DDD modeling approach to compare differences before and after 2012 as opposed to a hierarchical model to compare differences in readmission rates for TM and MA patients for each individual year. Finally, our risk-adjustment variables differed as well. Thus, our findings should be interpreted in the context of both our data source and modeling approach.

Our findings have important policy implications. Although most Medicare patients are still enrolled in TM, the growing share of MA patients means that CMS payment policies focused on TM patients will have a smaller impact than the past unless spillover occurs. Moreover, the fragmentation of MA plans means that no single quality reform will be universally adapted by all plans. Instead, CMS may be best served by continuing to emphasize measure harmonization, especially in those areas most likely to lead to systemic improvement.

Conclusion

The HRRP appears to be reducing readmissions for both TM and MA patients. However, we cannot fully discount that other MA policies or interventions could also have contributed to the decline in MA readmission rates. Our findings support the growing body of evidence on positive spillover effects of the HRRP. As federal policymakers continue to pursue payment reforms, they should consider focusing on conditions and outcomes most likely to generate spillover in order to benefit the greatest number of Medicare beneficiaries possible.

Figure 4. Unadjusted, Unplanned Readmission Rates by Condition and Medicare Enrollment Status, 2007-2014

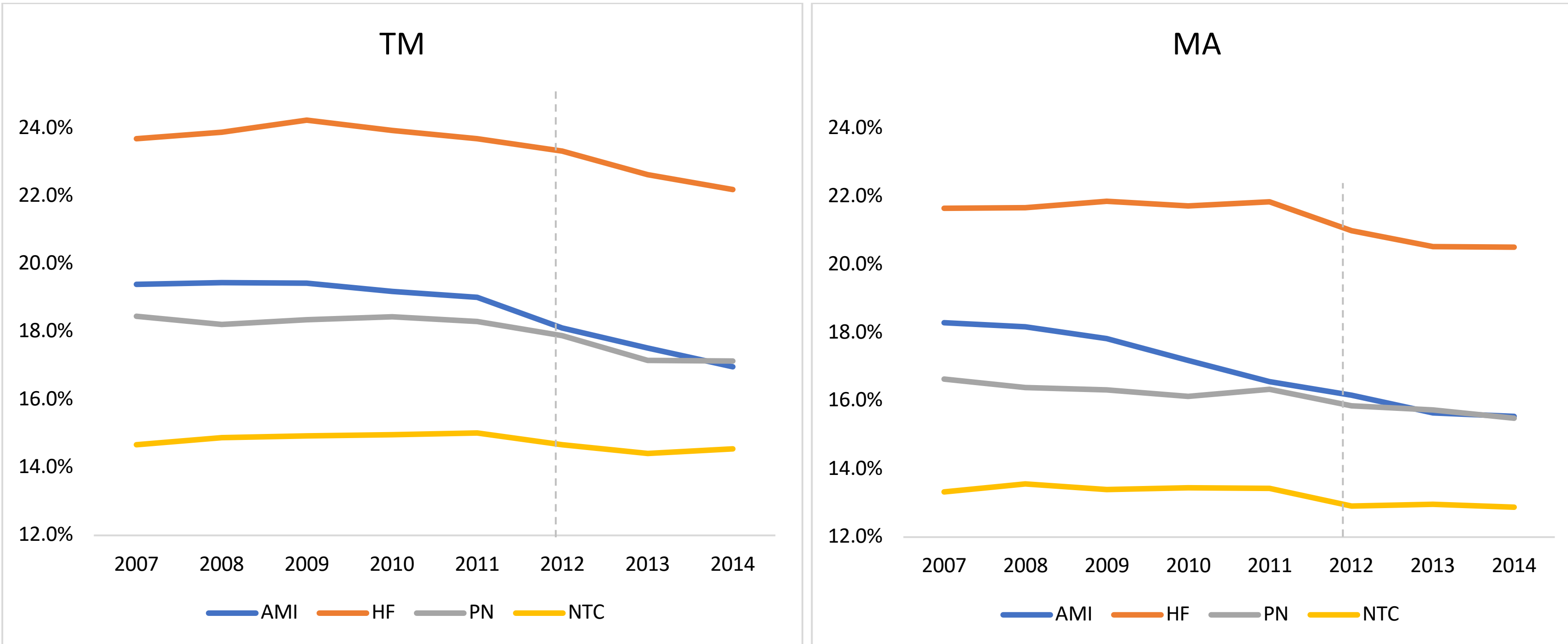


Table 4. Descriptive Statistics for TM and MA Admissions, 2007-2014

	TM	MA	P-Val
Index Admissions, N	10,171,499	4,324,233	
Age, Median (IQR)	79 (72-85)	78 (71-84)	<0.001
Female, N (%)	5,822,234 (57.3%)	2,396,623 (55.4%)	<0.001
Comorbidity, Mean (SD)	1.55 (1.14)	1.43 (1.10)	<0.001
Length of stay, Median (IQR)	4 (2-6)	3 (2-6)	<0.001
Race (uniform), N (%)			
White	7,474,516 (74.3%)	2,791,914 (65.2%)	<0.001
African-American	773,462 (7.7%)	512,898 (12.0%)	
Hispanic	1,090,053 (10.8%)	678,178 (15.8%)	
Asian/Pacific Islander	405,245 (4.0%)	152,308 (3.6%)	
Native American	19,362 (0.2%)	5,638 (0.1%)	
Other	296,135 (2.9%)	143,682 (3.4%)	
Patient Location, N (%)			
Large Metro (>=1,000,000)	6,591,637 (65.0%)	3,528,850 (81.7%)	<0.001
Small Metro (<1,000,000)	2,825,305 (27.8%)	679,929 (15.7%)	
Micropolitan	529,669 (5.2%)	81,673 (1.9%)	
Not metropolitan or micropolitan	201,935 (2.0%)	28,321 (0.7%)	
Median Income by County $, N (%)			
Quartile 1 (Poorest)	2,466,841 (24.8%)	1,081,768 (25.5%)	<0.001
Quartile 2	2,539,107 (25.5%)	1,102,505 (26.0%)	
Quartile 3	2,468,383 (24.8%)	1,128,602 (26.6%)	
Quartile 4	2,471,286 (24.8%)	931,391 (21.9%)	

Table 5. Changes in Readmission Rates After Implementation of the HRRP Relative to Changes in MA NTC Readmission Rates

	TM	95% CI	MA	95% CI
AMI	-1.0	[-1.3 , -0.6]***	-1.0	[-1.5 , -0.6]***
HF	-0.5	[-0.8 , -0.2]***	-0.5	[-0.9 , -0.1]**
PN	-0.3	[0.0 , -0.5]	0.0	[-0.3, 0.3]
NTC	0.2	[0.0, 0.3]*	N/A	N/A

*p<0.5, **p<0.01, ***p<0.001

Table 6. Changes in Readmission Rates After Implementation of the HRRP with Different Assumptions of the Impact of the HRRP on MA NTC Readmission Rates

	>50% of MA NTC Decline Due to HRRP				100% of MA NTC Decline Due to HRRP			
	TM	**95% CI**	**MA**	**95% CI**	**TM**	**95% CI**	**MA**	**95% CI**
AMI	-1.3	[-1.6 , -0.9]***	-1.1	[-1.6 , -0.7]***	-1.5	[-1.9 , -1.1]***	-1.4	[-1.9 , -1.0]***
HF	-0.8	[-1.1 , -0.5]***	-0.6	[-1.0 , -0.2]***	-1.1	[-1.3 , -0.8]***	-0.8	[-1.3 , -0.5]***
PN	-0.5	[-0.8 , -0.3]***	-0.1	[-0.3, 0.0]*	-0.8	[-1.1 , -0.5]***	-0.4	[-0.8 , 0.0]*
NTC	-0.1	[-0.3 , 0.0]*	-0.2	[-0.4 , -0.1]***	-0.4	[-0.5 , -0.3]***	0.0	[0.0, 0.0]

*p<0.5, **p<0.01, ***p<0.001

CHAPTER 4. THE ASSOCIATION OF READMISSION REDUCTION ACTIVITIES WITH PRIMARY CARE PRACTICE READMISSION RATES

Overview

Importance: Medicare has steadily introduced readmission measures into a growing number of value-based purchasing programs. The implementation of the Quality Payment Program means that Medicare reimbursement for many primary care practices (PCPs) may now be impacted by readmission rates for their patients. However, there remains an important gap examining how PCPs can lower readmission rates.

Objective: To examine the relationship between PCPs' number of readmission reduction activities and their risk-standardized readmission rates (RSRRs).

Design, Setting, and Participants: A retrospective study of 1,788 PCPs with 415,663 hospital admissions for 2016. We constructed mixed-effects logistic regression models to estimate PCP-level RSRRs. We then used a linear regression model to correlate PCPs RSRRs with their number of readmission reduction activities, controlling for PCP ownership status, number of total physicians, Census region, urban/rural status, and percent of patients who are dual-eligible.

Exposures: Standardized composite score, ranging from 0-1, for PCPs' total number of readmission reduction capabilities.

Main Outcomes and Measures: The association between PCPs' standardized composite score and their RSRR.

Results: PCPs' number of readmission reduction activities was significantly associated ($P < .05$) with lower RSRRs. On average, PCPs experienced a 0.05 percentage point decrease in RSRR for each additional activity. RSRRs for PCPs with more than 20 physicians were 0.38 percentage points higher than PCPs employing 3-5 physicians ($P < .05$). Each percentage point increase in PCPs' percentage of dual-eligible patients was associated with a 0.01 percentage point increase in RSRR ($P < .01$). Urban PCPs had significantly lower RSRRs than large rural (-0.39 percentage points; $P < .05$), small rural (-1.71 percentage points; $P < .001$), and isolated PCPs (-1.35 percentage points; $P < .01$).

Conclusions and Relevance: PCPs' scores on the readmission reduction activities composite measure was significantly associated with lower RSRRs. PCPs' RSRRs declined as they engaged in more of these activities. This relationship was stronger for PCPs with at least 200 admissions, a group that will be required to report on readmissions as part of the Quality Payment Program.

Introduction

The concept of reducing medically unnecessary readmissions in order to improve quality and reduce spending has been around for decades.[1,2] However, only recently have policymakers introduced readmission measures into Medicare's value-based purchasing programs. The first, and still most visible, of these programs was the Hospital Readmissions Reduction Program (HRRP), implemented in 2012.[3] Since then, Medicare has also added readmission measures into a variety of other value-based purchasing programs directed at skilled nursing facilities[4], dialysis centers[6], accountable care organizations,[8] and home health care.[5] Until recently, Medicare has not assessed readmission rates for physician practices. The implementation of the Quality Payment Program (QPP) in 2017 means this is no longer the case.[7]

The increased attention from Medicare and other payers to reducing readmissions has led to a burgeoning literature exploring the most effective strategies for achieving that goal. These studies can be classified into three major types. The first is focused on improving care transitions. Care transitions interventions often occur in health systems and study the impact of coordinating care across both inpatient and outpatient providers.[39,41,99] While practices play an integral role, they are not the sole focus. The second examines hospitals and their ability to reduce readmission rates.[42–45,75,100,101] These studies may include aspects that involve practices but they typically operate on the periphery of the intervention. The third explores individual practices and patient-centered medical homes. The interventions are usually conducted in practices affiliated with academic medical centers and their findings may not be generalizable to a larger population of practices.[52,102–104]

Even with such a large evidence base on readmission reduction strategies, there remains an important gap, especially at the primary care practice (PCP) level.[52] PCPs play an integral role in reducing readmissions[105,106] but we have only limited knowledge of how activities conducted solely within the walls of PCPs are associated with reduced readmission rates for their patients. The few PCP studies we do have are often based on small-scale interventions conducted in one, or a handful, of organizations. While these are important contributions to the literature, their findings may not be externally valid.[52,53] To the best of our knowledge, there are no studies examining the association of PCP activities and readmission rates in a large and diverse number of PCPs. With QPP payment adjustments increasing to a maximum of nine percent in 2022, there is a growing need to address this issue.

We attempt to fill this gap by examining the relationship between PCP readmission reduction activities and readmission rates for their patients in a sample of over 1,700 PCPs. We combined Medicare claims data with a nationally representative PCP survey to create a composite readmission reduction measure based on our conceptual model of how PCP readmission reduction activities influence readmission rates. Based on our conceptual mode, we hypothesized that implementing more of these activities would be associated with lower PCP readmission rates.

Conceptual Model

Although we are aware of no large scale studies linking PCP interventions with readmission rates, we can attempt to extrapolate potentially useful strategies from the literature. While readmission reduction approaches vary greatly depending on the care setting and study design, they share some common aspects. These include tasks like: communicating with patients within 72 hours of discharge,[101] providing home visits after discharge,[45] sending discharge summaries to primary care physicians,[39] establishing a standardized process to reconcile medication,[52,107] ensuring patients have access to their primary care provider,[39] and empowering a care manager to help patients adhere to care plans.[41,76,100] Moreover, interventions with more readmission reduction activities demonstrate the most significant declines in readmission rates.[45,52,107–109] Thus, the total number of activities may be just as, if not more, vital than the type of activity when attempting to reduce readmission rates.

Based on these findings, we constructed a conceptual model illustrating the different factors that potentially influence PCP readmission rates (Figure 1). The top half of the model is composed of PCP-level activities. We have categorized these into four distinct domains: care management, patient education, addressing social needs, and using data for quality improvement. Under each domain we list specific readmission reduction activities. These are not meant to be exhaustive but they do represent tasks most commonly employed in the readmission reduction literature. Each of our domains may independently lead to reduced readmissions but the literature suggests they are most successful when combined. On the bottom half of the conceptual model we list patient and organizational-level factors that influence readmission rates but are outside of a PCP's control. We believe these factors should be adjusted for as much as possible when modeling PCP-level readmission rates.

Study Data and Methods

Data

We relied on the National Survey of Healthcare Organizations and Systems (NSHOS) to obtain PCP-level activities potentially associated with readmission. The NSHOS is a nationally representative survey, conducted from 2017-2018, of primary care and multi-specialty physician practices.[110] The NSHOS employed a stratified-cluster sampling design to survey health systems, hospitals, and physician practices with three or more primary care physicians on a wide range of organizational characteristics and capabilities. The sample frame was derived from IQVIA's OneKey database, which includes information on more than 9.6 million healthcare workers at over 700,000 healthcare organizations.[111] The NSHOS oversampled practices from several categories to ensure reliable estimates for myriad practice types, including practices participating in accountable care organizations, the High Value Healthcare Collaborative, and the National Survey of Physician Organizations. We evaluated 2016 readmissions using 100% inpatient and outpatient Medicare claims data from 2015 and 2016.

Sample

The NSHOS initially identified 4,976 practices that met inclusion criteria. Of these, 2,333 (47%) completed the survey; 143 of the responding practices were excluded because it could not be confirmed that they were in the survey sample frame. After merging 2017-2018 NSHOS data with 2015-2016 Medicare data using patients' beneficiary ID number and PCPs' tax identification number, another 117 PCPs were excluded because no patients were assigned to them. Finally, in order to create reliable estimates, we restricted our sample to PCPs with at least 25 index admissions. The final sample included 1,788 practices and 415,663 admissions from all 50 states and Washington DC. Patients were included in our sample if they were 65 and older, continuously enrolled in Medicare Parts A and B 12 months prior to and including the date of the index readmission, and enrolled in Part A for at least 30 days after the date of discharge. We include comparisons of PCP and patient-level characteristics for survey respondents and non-respondents in our Appendix Tables A1 and A2.

Patient Attribution

We attributed patients to practices by mirroring the approach used in the Medicare Shared Savings Program.[112] We assigned patients to practices based on where they received the plurality of their evaluation and management visits. If a patient did not have any primary care visits during the year, we attributed them to the specialist practice where they received the plurality of their evaluation and management visits.

Outcome

We modeled our outcome using CMS's hospital-wide readmission measure methodology.[84] A readmission was defined as any unplanned admission occurring within 30 days of a previous index admission. We excluded index admissions for patients who died during hospitalization, were discharged against medical advice, were admitted for psychiatric, cancer, or rehabilitation treatment, or were no longer enrolled in Medicare Part A at least 30 days after discharge. We combined stays into a single continuous hospitalization if a patient was discharged from one hospital and admitted the same or next day to another hospital. Unlike CMS's condition-specific readmission measures, a readmission can serve as both a readmission and an index admission in the hospital-wide readmission measure. For example, if a patient were admitted on January 1 and readmitted on January 20, the January 20 admission would count as a readmission for the January 1 hospitalization and an index admission for future hospitalizations. We distinguished between planned and unplanned readmissions by applying CMS's planned readmission algorithm 4.0.[84]

Independent Variable

Our independent variable of interest was practices' total number of readmission reduction activities. We created this composite measure by first identifying 30 candidate variables from the survey, representing all four domains of our conceptual model (full list in Appendix Table A3). We dichotomized Likert scale questions by recoding "never", "sometimes", and "often" as zero and "always" as one; this was consistent with our conceptual model that is based on practices performing readmission reduction activities for all, not most, patients. We then reviewed the interitem correlations of each candidate variable, assuming tetrachoric correlations, to arrive at a list of mutually exclusive variables. We narrowed our final list to 12 variables (Table 1). Nearly all variables had interitem correlations under 0.3 and only one was above 0.5 (0.53), indicating the measures were capturing separate care components.

Next, we created a standardized score for our composite measure ranging from 0-1. The numerator was the total number of survey questions for which a practice responded yes or always; the denominator was the total number of survey questions without missing data for that practice. We used this method for the denominator so that practices that did not respond to all 12 survey questions were not penalized for missing data. We excluded any practices that responded to fewer than seven questions. More than 93% of practices responded to 11 or 12 of the questions and only 14 were excluded for responding to fewer than seven.

Statistical Analyses

We compared patient and PCP characteristics by quartiles of PCP-level observed (unadjusted) readmission rate. We compared means for normally distributed continuous variables using t-tests. When continuous variables were not normally distributed, we employed Mann-Whitney U tests. We used chi-square tests to compare groups on binary and categorical variables.

We calculated PCPs' risk-standardized readmission rates (RSRR) for hospital-wide readmissions using a mixed effects logistic regression model, modeling patient readmissions as a dichotomous outcome. We adjusted this model for patient race, median income of a patient's census tract, frailty, and hierarchical condition category (HCC) score. We then replicated CMS's method for calculating PCPs' predicted over expected readmission rates.[84] The predicted readmission rate is based on each PCP's patient characteristics and their PCP intercept. The expected readmission rate is based on each PCP's patient characteristics and the overall mean PCP intercept. This results in a standardized readmission ratio which we then multiplied by the observed readmission rate for all patients to arrive at PCPs' RSRRs.

After calculating PCPs' RSRRs, we estimated a PCP-level linear regression model with RSRRs as the outcome. Our independent variable of interest was a continuous variable representing PCPs' readmission composite measure score, which ranged from 0-1. We included control variables for PCP ownership status, number of total physicians, Census region, urban/rural status, and percent of patients who are dual-eligible. We applied survey weights for all analyses. We conducted all analyses in Stata 16.0. This study was deemed exempt by our institution's internal review board.

Sensitivity Analyses

We constructed our independent variable based on our conceptual model. We then estimated our PCP-level linear regression model using this definition. However, in post-hoc analyses we also examined several other specifications of our independent variable. We estimated our PCP-level linear regression model with covariates for each individual survey question, as opposed to a composite score. We also conducted principal component analysis using all 30 original candidate measures as well as the 12 measures included in our final composite. We also revised our composite measure to only include activities that were negatively associated with RSRRs, using a data-driven approach as opposed to solely relying on our theory. Finally, we restricted all our models to practices with at least 200 admissions in order to be consistent with the QPP.

Results

PCP and Admission Characteristics

When comparing PCPs by quartile of observed readmission rates, we noticed several key differences (Table 2). Observed readmission rates increased as PCPs cared for greater numbers of admitted patients. PCPs in the lowest quartile of observed readmission rates were more likely to be independently owned, employ 3-5 physicians, be located in urban areas, or operate in the West. We also observed increases in PCPs' percentage of dual-eligible patients when moving from lower to higher quartiles. Admissions attributed to PCPs in each quartile were fairly similar in age, sex, and race across all four quartiles. We observed monotonically increasing values for disability, frailty, and HCC score when moving from the first to fourth quartile. The inverse was true for median income.

Practice-Level Model

Our main independent variable of interest, the readmission activities composite, was significantly associated ($P < 0.05$) with lower RSRRs. We observed a 0.05 percentage point decrease in RSRRs for each additional activity in our composite measure that a PCP engaged in, holding all other factors constant (Table 9). Engaging in more readmission reduction activities was associated with lower RSRRs (Figure 6). On average, RSRRs for practices with composite scores between 0.8-1.0 were one percentage point lower than practices that engaged in none of the activities in our composite measure.

RSRRs for PCPs with more than 20 physicians were 0.37 percentage points higher than PCPs employing 3-5 physicians ($P < .05$). Compared with PCPs in the East, RSRRs for PCPs in the West were 0.40 percentage points lower ($P < .01$). Urban PCPs had significantly lower RSRRs than large rural (-0.40 percentage points; $P < .05$), small rural (-1.73 percentage points; $P < .001$), and isolated PCPs (-1.38; $P < .001$). Each percentage point increase in PCPs' percentage of dual-eligible patients was associated with a 0.01 percentage point increase in RSRR ($P < .01$). We did not observe a significant relationship between practice ownership category and RSRR. We include the results of our mixed-effects model in Appendix Table A4 and Figure A1.

Sensitivity Analyses

When we estimated our linear regression model with covariates for each individual survey question, as opposed to a composite score, we found that nine of them were negatively associated with readmissions but none of the 12 individual survey questions was statistically significant ($p<0.05$). This suggests that reductions in readmission rates were not driven by one or two activities. Principal component analysis using all 30 candidate measures resulted in seven factors with eigenvalues above 1.0. None of these factors was significantly associated ($p<0.05$) with lower RSRRs when we jointly controlled for all seven. Principal component analysis of the 12 measures included in our final composite measure resulted in three factors with eigenvalues above 1.0 and again, none of the factors was significant ($p<0.05$). We then modeled RSRRs as a function of a revised composite score with only the nine tasks negatively associated with RSRRs. As expected, the effect of the composite score increased, from

-0.05 to -0.08. Finally, the effect size of the composite score measure nearly doubled, and remained statistically significant, when we limited our sample to practices with at least 200 admissions.

Discussion

We found that PCPs with more readmission reduction activities experienced lower RSRRs. This relationship was statistically significant and supports our hypothesis. Prior studies have also demonstrated this effect at the hospital-level,[45] across the continuum of care (hospitals, practices, and community services),[108] or for individual practices and health systems.[52,107] However, our finding is novel because it includes over 1,700 PCPs and only incorporates capabilities directly under the control of PCPs. This association was nearly twice as strong when we further limited our analysis to only practices with at least 200 admissions, consistent with the QPP minimum case size requirement.

Our findings have several important implications. First, while each of the activities in our composite measure was a component of commonly successful readmission reduction interventions, none was significantly correlated with lower RSRRs by itself. Instead, increasing reductions in readmission rates occurred as PCPs performed more activities. Average RSRRs for PCPs performing almost all or all of the activities in our composite measure were a full percentage point lower than RSRRs for PCPs engaging in none of the activities. A one percentage point change in RSRR was the difference between being classified in the 50^{th} or 75^{th} percentile of RSRR. One possible explanation for this finding is that successfully reducing readmissions may depend on a multitude of activities. This may explain why multi-component interventions have proven to be the most effective at reducing readmissions.[94] However, we acknowledge the possibility that PCPs implementing more activities do so because of a strong readmission reduction culture or greater financial/human resources. These latent variables may be just as, or more, vital than the number of activities.

Second, we found that PCPs employing over 20 physicians were significantly more likely to have higher RSRRs, even after controlling for their readmission reduction activities composite score. This is consistent with previous studies demonstrating that practices employing fewer physicians performed better on readmissions than practices with larger numbers of physicians.[113,114] It may be that smaller practices are more nimble than larger practices and can more easily adjust their activities based on their patients' needs. It is also possible that ensuring all physicians regularly engage in these activities is easier when there are fewer clinicians. While many smaller practices performed better in our study, most will be exempt from the requirement to report on readmissions as part of MIPS.[7] Moreover, the overall percentage of small (2-5 physicians) or solo practices has been rapidly decreasing, from 51.5% in 2012 to 41.2% in 2018.[115] During this same period, the percentage of practices with at least 30 physicians increased from 19.9% to 27.5%. This trend may be accelerated by the COVID-19 pandemic which is putting increased financial strain on practices, many of which are experiencing decreases in revenue of over 50%.[116] Thus, the number of practices that are well suited because of their smaller size to reduce readmissions could continue to shrink, possibly at an even faster rate than before COVID-19.

Third, our findings highlight the possibility that the current risk-adjustment methodology used by CMS may not properly capture all patient-risk factors. We observed significantly higher RSRRs for both rural PCPs and PCPs caring for more dual-eligible patients. It is possible that these providers truly do perform worse on readmissions. However, it is also conceivable that patient factors like distance from their PCP[117] and lower education or income[30] make it more difficult to prevent these patients from being readmitted. CMS initially opposed adjusting quality measures for these types of socioeconomic variables on the basis that it would hold providers to different standards of care based on their patients' demographics.[73] However, CMS has since revised that stance. The HRRP now splits hospitals into peer groups based on their percentage of dual-eligible patients. And the MIPS includes a complex patient bonus of up to five points based, in part, on the percentage of a clinician's patients who are dual eligible.[118] Moreover, the MIPS excludes many rural providers since the program does not apply to rural health clinics or federally qualified health centers. While this approach is welcome, not all rural practices will be excluded and the MIPS complex patient bonus may not fully account for the effect of caring for dual-eligible patients.[38,119] Moving forward, it will be important for CMS and others to monitor their approach to ensure that rural clinicians and practices in addition to those caring for high percentages of dual-eligible patients are not disproportionately penalized as part of the MIPS.

Finally, although routinely engaging in multiple readmission reduction activities can help reduce readmission rates, it may not be at the top of many PCPs' agenda. Over two-thirds of physicians are exempt from the MIPS, and only practices with at least 200 inpatient admissions and 16 or more clinicians are required to report on readmissions.[7] Moreover, performance on readmissions represents a tiny proportion of the overall MIPS score and, depending on the APM, readmission performance may be even less important. Even though CMS increasingly incentivizes physicians and their practices to reduce readmissions, there still may not be a business case for PCPs to invest significant resources into activities like hiring care managers or conducting home visits. This is especially true if these investments do not also improve performance on the ever growing number of other quality measurement requirements.

We acknowledge several limitations when interpreting our findings. First, fewer than half of PCPs responded to the NSHOS. While PCPs responding to the survey were similar to non-respondents on several key observable characteristics, our sample may not be representative of the general population. Second, as with any survey there is always the possibility of measurement error, which could bias our estimates. In general, this would cause attenuation bias, thus the fact that our composite measure was significant, even in the presence of measurement error, is reassuring. Third, our survey is based on 2017-2018 data but we assessed readmissions for patients admitted in 2016. If PCPs' readmission reduction activities significantly changed from 2016 to 2017-2018, our findings may not accurately assess the relationship between readmission reduction activities and readmission rates. Fourth, the NSHOS survey does not include PCPs with fewer than three physicians, which limits generalizability. Fifth, since our study was cross-sectional there is the possibility for omitted variable bias and our findings do not allow us to infer causality. Finally, our study was conducted prior to the COVID-19 pandemic which could create a healthcare landscape dramatically different than the one that existed before the outbreak.

Conclusion

Routinely engaging in a greater number of readmission reduction activities was significantly associated with lower PCP-level RSRRs. This size of this association almost doubled when we limited our sample to practices with at least 200 admissions. We also observed that practices employing more than 20 physicians, rural practices, and practices caring for larger proportions of dual-eligible patients had higher average RSRRs. CMS and other payers should ensure they are properly accounting for factors that may be outside of PCPs' control when implementing payment policies based on readmissions.

Table 7. Questions Included in Composite Measure of Readmission Reduction Capabilities

Care Management
Is a care manager involved in helping high-risk patients adhere to their care plan?
Does your practice routinely conduct home visits after high-risk patients are discharged from the hospital?
Does your practice routinely receive discharge summaries within 72 hours of hospitalization for high-risk patients?
Does your practice have a standardized process to reconcile medications for high-risk patients discharged from the hospital?
Patient Education
Does your practice have a system in place to routinely screen patients for health literacy?
Do clinicians routinely engage in shared-decision making with patients?
Does your practice collect patient-reported measures of patient activation?
Addressing Social Needs
Does your practice routinely refer high-risk hospitalized patients to community health-related social services?
Does your practice currently use any culturally tailored programs or interventions?
Using Data for Quality Improvement
Does your practice use data on hospital admissions or readmissions for internal use/quality improvement efforts?
Does your practice use data to modify the discharge planning process as needed?
Does your practice base clinician performance, in part, on patient readmissions or use of other acute care services?

Table 8. Patient and Hospital Characteristics by Observed Practice Readmission Rate Quartile

Practice Characteristic	Quartile 1	Quartile 2	Quartile 3	Quartile 4	*P* Value
N	**447**	**447**	**452**	**442**	
Index Admissions, mean(SE)	119.36 (95.32)	216.17 (217.93)	296.79 (449.21)	297.59 (413.84)	<0.001
Raw Readmission Rate, %(SE)	7.87 (2.12)	11.89 (8.53)	15.01 (9.60)	20.49 (3.80)	<0.001
Ownership, N(%)					
Independent	155 (34.75)	121 (27.19)	128 (28.51)	117 (26.59)	
A larger physician group	44 (9.87)	56 (12.58)	47 (10.47)	50 (11.36)	
A hospital	58 (13.00)	61 (13.71)	76 (16.93)	79 (17.95)	0.006
A healthcare system	175 (39.24)	185 (41.57)	180 (40.09)	158 (35.91)	
Other	14 (3.14)	22 (4.94)	18 (4.01)	36 (8.18)	
Number of Physicians, N(%)					
3-5	187 (41.83)	147 (32.89)	143 (31.64)	147 (33.26)	
6-20	205 (45.86)	224 (50.11)	215 (47.57)	202 (45.70)	0.001
21+	55 (12.30)	76 (17.00)	94 (20.80)	93 (21.04)	
Census Region					
Northeast	84 (18.79)	84 (18.79)	90 (19.91)	109 (24.66)	
Midwest	131 (29.31)	137 (30.65)	130 (28.76)	145 (32.81)	<0.001
South	109 (24.38)	127 (28.41)	155 (34.29)	117 (26.47)	
West	123 (27.52)	99 (22.15)	77 (17.04)	71 (16.06)	
Rural-Urban Commuting Area, N(%)					
Urban	409 (91.50)	385 (86.13)	362 (80.09)	331 (74.89)	
Large Rural	22 (4.92)	39 (8.72)	62 (13.72)	41 (9.28)	<0.001
Small Rural	12 (2.68)	18 (4.03)	18 (3.98)	56 (12.67)	
Isolated	4 (0.89)	5 (1.12)	10 (2.21)	14 (3.17)	
%Patients Dual-Eligible, mean(SE)	11.91 (14.18)	12.99 (13.95)	19.24 (17.30)	27.91 (20.07)	<0.001
Admission Characteristic					
N	**53,352**	**96,627**	**134,151**	**131,533**	
Age, mean(SE)	77.18 (7.95)	77.37 (7.95)	77.84 (8.09)	78.41 (8.28)	<0.001

Female, N(%)	29,916 (56.07)	53,934 (55.82)	75,705 (56.43)	75,931 (57.73)	<0.001
Race, N(%)					
White	48,048 (90.06)	88,106 (91.18)	119,513 (89.09)	115,086 (87.50)	
Black	2,776 (5.25)	4,692 (4.90)	9,377 (7.03)	11,555 (8.83)	<0.001
Other	2,060 (3.90)	3,049 (3.18)	4,440 (3.33)	4,178 (3.19)	
Disabled or on ESRD, N(%)	6,047 (11.33)	11,952 (12.37)	19,563 (14.58)	22,889 (17.40)	<0.001
HCC score, mean(SE)	2.34 (1.60)	2.53 (1.71)	2.81 (1.85)	3.22 (2.03)	<0.001
Frailty, mean(SE)	0.78 (1.21)	0.83 (1.25)	0.98 (1.37)	1.33 (1.62)	<0.001
Income ($), median(IQR)	58109 (44222-77177)	56016 (44580-73140)	52569 (40677-68929)	50488 (39293-66667)	<0.001

Table 9. Linear Regression Results of Practice-Level 2016 Readmission Rates

	Coefficient	SE	P Val
Readmission Composite	-0.520	0.260	0.046
Ownership (ref. group Health System)			
Independent	-0.051	0.123	0.679
Physician Group	-0.023	0.163	0.819
Hospital	0.230	0.160	0.152
Number of Physicians (ref. group 3-5)			
6-20	0.058	0.115	0.617
20+	0.365	0.158	0.021
Ownership (ref. group Northeast)			
Midwest	-0.082	0.140	0.555
South	-0.092	0.134	0.494
West	-0.404	0.140	0.004
RUCA (ref. group Urban)			
Large Rural	0.401	0.194	0.038
Small Rural	1.725	0.350	<0.001
Isolated	1.382	0.564	0.014
% Patients Dual-Eligible	0.010	0.327	0.003

Figure 5. Conceptual Model

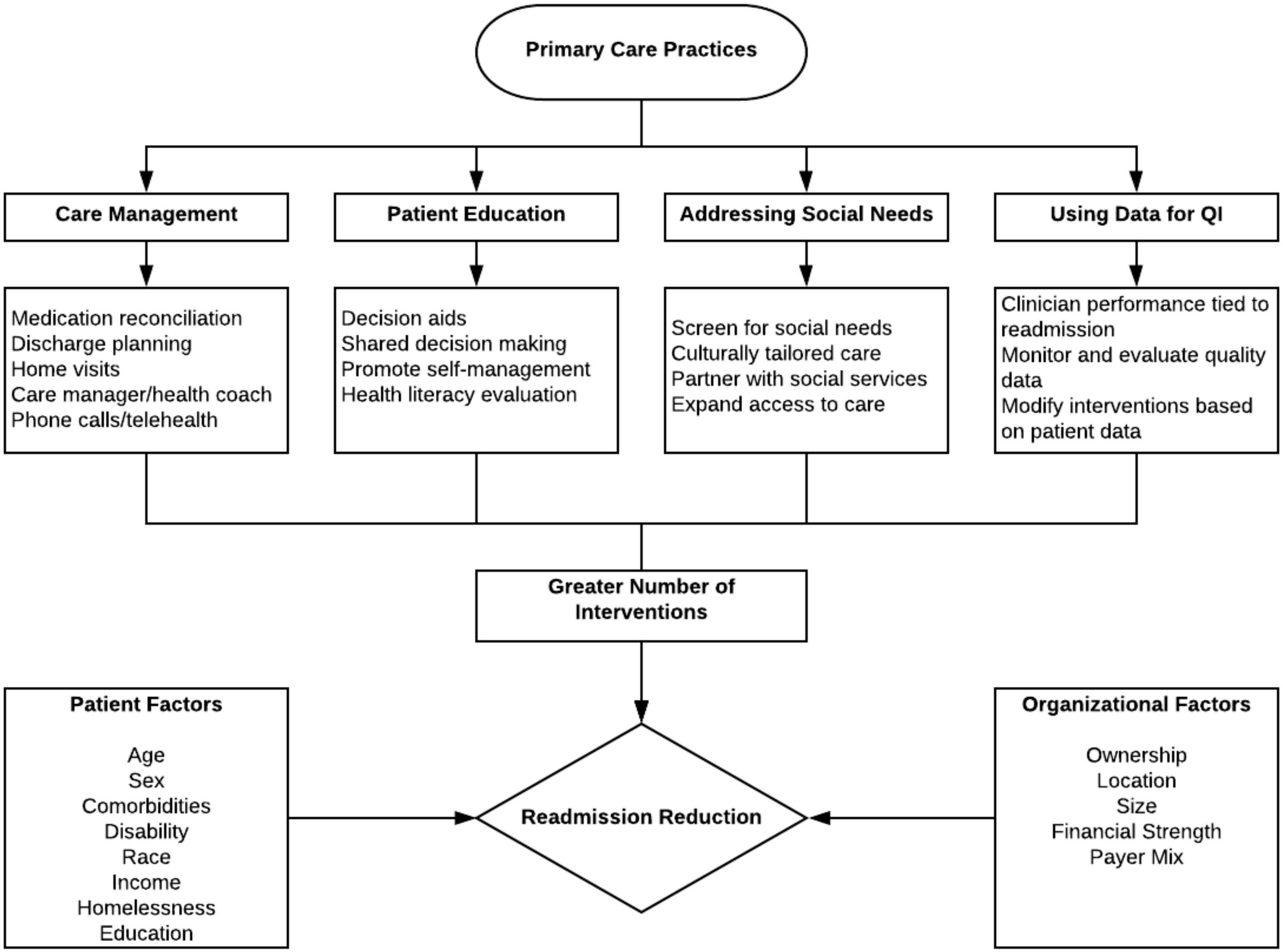
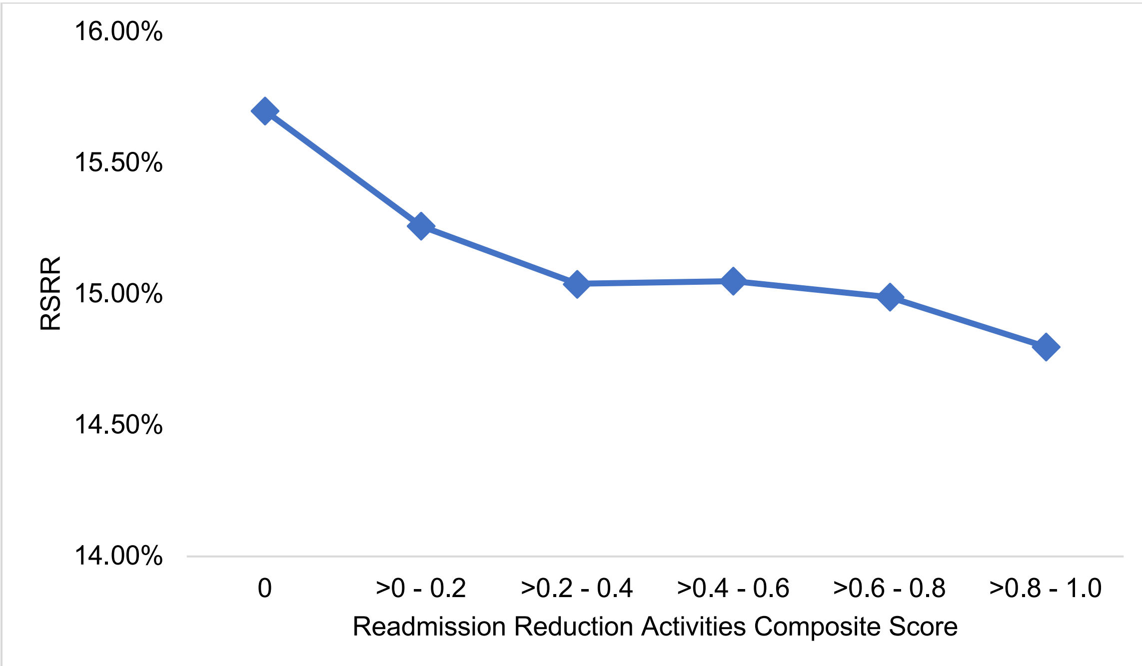


Figure 6. Association of Readmissions Reduction Activities Composite Score and RSRRs



CHAPTER 5. CONCLUSION

Summary of Findings

This dissertation investigated the topic of hospital readmissions from several perspectives. It analyzed the role of financial incentives in motivating recent declines in Medicare readmission rates. It explored the possibility of spillover effects for patients who are not subject to Medicare's readmission policies. Finally, it explored whether activities conducted in primary care practices could help reduce their patients' readmission rates. Below I summarize the main findings of each of the three aims. I then highlight several policy implications of my findings and suggest topics for future research.

In the first aim, I demonstrated that the size of HRRP's payment adjustments do not appear to be associated with declining Medicare readmission rates. Facing the potential of larger HRRP payment adjustments was not associated with lower ERRs. While the financial incentives associated with the HRRP may have acted as a triggering mechanism to signal hospitals on the need to reduce readmissions, I did not observe a direct relationship between the size of the incentive and performance on readmissions. This finding challenges the notion that in order for P4P programs to be successful they must use large payment adjustments.[120,121] It is also possible that the HRRP's payment penalties are too small to incentivize differential performance based on penalty size and larger maximum penalties would have a greater influence on readmissions.

In the second aim, I found that the HRRP has led to significant declines in readmission rates for patients admitted for conditions both targeted and not targeted by the HRRP. Readmission rates for both TM and MA patients were significantly lower after implementation of the HRRP, indicating the presence of policy spillover. I found the greatest evidence of spillover for patients admitted for either AMI or HF, with less evidence of spillover for PN patients or TM patients admitted for NTCs. The results of this study add to the growing literature showing HRRP spillover for non-TM patients. They also raise the possibility that many hospitals do not have the capacity or resources to selectively target their readmission reduction activities to only TM patients and instead focus their efforts on a strategy aimed at reducing readmissions for all patients.

In the third aim, I found that PCPs that regularly engage in numerous readmission reduction activities are more likely to reduce their patients' readmission rates than practices that participate in fewer activities. I also found that certain PCP characteristics like employing fewer physicians, caring for fewer dual-eligible patients, and operating in an urban setting are associated with lower readmission rates. There is strong face validity that PCPs play a central role in reducing readmissions and my results support this concept.

Policy Implications

While all three dissertation aims focused on the topic of readmissions, each of them has distinct policy implications. First, the fact that facing larger potential HRRP payment adjustments was not associated with lower readmission raises the question of how Medicare should view the role of financial incentives in its value-based purchasing programs. Given that readmission rates initially declined after HRRP's implementation, federal policymakers may not be concerned with whether this was due to the HRRP's payment adjustments or some other factor related to the program. Nevertheless, with readmission declines slowing down in more recent years, it is important for policymakers to understand the reasons for the HRRP's initial success in order to determine if modifications to the program need to be made to reaccelerate declines in readmissions.

Second, the presence of spillover in the HRRP suggests policymakers should explore if any lessons can be applied to other care settings or quality areas. This has important policy implications since Medicare continues to embrace value-based purchasing.[57] If existing or future Medicare programs are able to generate similar amounts of spillover, then there is the potential for Medicare to more strongly influence quality and resource use throughout the health care system. It is possible that reducing readmissions is an activity that is more likely than others to produce spillover, making it harder to replicate this success in other measures or programs. Conversely, the HRRP may have led to spillover because it is a simple program to understand and relies on interventions that are less likely to only be applied to TM patients.[122,123] If it is more of the latter, Medicare could benefit from designing other value-based purchasing programs after the HRRP. Programs that demonstrate spillover for MA patients should be closely scrutinized as Medicare patients are increasingly deciding to enroll in MA instead of TM.

Third, primary care is an important care setting to target if policymakers wish to further reduce readmission rates for Medicare patients. I found that engaging in more readmission reduction activities may help PCPs lower their readmission rates. However, many of these activities are costly in terms of time and money and there may not be a business case for PCPs to invest the resources needed to successfully implement these activities. Insomuch as policymakers view reducing readmissions as central to Medicare's mission, it may make sense to investigate options for incentivizing PCPs to adopt more readmission reduction activities. However, it appears that Medicare administrators believe that, similar to the HRRP, financial incentives will motivate practices to lower readmission rates. Medicare includes a readmission measure in the QPP. But the QPP is vastly more complex than the HRRP and the readmission measure in the QPP only applies to a small percentage of practices. It is possible, that like the HRRP, the inclusion of a readmission measure in the QPP will send a signal to all PCPs that reducing readmissions is important. If this is not the case, then reducing PCP readmission rates may be more feasible if Medicare follows the recommendations I list here.

Future Research

While the results of this dissertation fill important gaps in the readmissions literature, future research is needed to expand on these findings. First, though this dissertation demonstrated that incentive size may not dictate performance on hospital readmissions, I only examined a single program. Policymakers are constantly expanding Medicare value-based purchasing programs and we still know relatively little about how performance on these programs relates to payment adjustments. We need more studies examining the relationship between performance and incentive size over longer periods of time. We also need qualitative studies examining provider perception of these financial incentives. We know very little about how hospitals, clinicians, and other health care workers view these incentives, which may help to explain why some value-based purchasing programs lead to improvement while others do not.

Second, while this dissertation demonstrated spillover effects of the HRRP for MA patients it only investigated readmissions for patients in three states, California, Florida, and New York. These are three of the most populous states but they still represent a minority of MA patients. These findings would be even more convincing if they were replicated in a national sample of MA patients, relying on the same methods I used in Chapter 3. Moreover, we need more studies examining spillover of Medicare value-based purchasing programs in general. Programs like the Hospital-Value Based Purchasing Program, Hospital-Acquired Condition Program, Quality Payment Program, and Skilled Nursing Value-Based Program all apply to only TM patients but may also impact the quality of care for MA patients. The need for this research is vital as MA enrollment continues to increase even as Medicare value-based purchasing programs remain almost entirely focused on TM patients.

Third, the research on primary care activities associated with lower readmission rates is an important contribution to the literature. Yet, because it is the first of its kind we need future research to corroborate these findings. It would be beneficial to see similar studies replicated with either more years of data or in more practices in order to confirm the findings. It is also important to conduct research investigating cultural and financial characteristics of practices and their relationship between both readmission reduction activities and readmission rates. Another avenue is to test whether or not the quality of the activities, as opposed to the number, also predicts readmission rates. It would also be intriguing research to examine how much hospitals influence readmissions versus practices. For example, does a practice with low readmission rates perform well because of what they do to reduce readmissions, or because most of their patients are admitted to a hospital that performs well on readmissions.

In conclusion, Medicare readmission policies have impacted multiple levels of the US health care system, from patients to practices to hospitals. There is reason to believe Medicare will play an even bigger role in reducing readmissions in the future with the inclusion of readmission measures in many of Medicare's newer value-based purchasing programs. This dissertation suggests that the success of these initiatives could depend on aspects like the incentive structure of the programs, the ability to generate spillover, and the likelihood of providers incorporating large numbers of readmission reduction activities.

APPENDIX

Appendix Table A1. ICD-9 Codes used to Define Cohorts

AMI	HF	PN	NTC
410.00	402.01	480.0	81.51
410.01	402.11	480.1	81.54
410.10	402.91	480.2	491.21
410.11	404.01	480.3	491.22
410.20	404.03	480.9	491.9
410.21	404.11	481	492.8
410.30	404.13	482.0	493.20
410.31	404.91	482.1	493.21
410.40	404.93	482.2	493.22
410.41	428.0	482.30	496
410.50	428.1	482.31	51881*
410.51	428.20	482.32	51882*
410.60	428.21	482.39	51884*
410.61	428.22	482.40	7991*
410.70	428.23	482.41	
410.71	428.30	482.42	
410.80	428.31	482.49	
410.81	428.32	482.81	
410.90	428.33	482.82	
410.91	428.40	482.83	
	428.41	482.84	
	428.42	482.89	
	428.43	482.9	
	428.9	483.0	
		483.1	
		483.8	
		485	
		486	
		487.0	
		488.11	
		507.0	

*These are only included when there is a secondary diagnosis of 491.21, 491.22, 493.21, or 493.22

Appendix Table A2. Risk Adjustment Variables for Comorbidities Present on Index Admission

CC Name	CC Number
Severe Infection	1, 3-6
Metastatic cancer and acute leukemia	8
Severe cancer	9, 10
Other cancers	11-14
Diabetes mellitus (DM) or DM complications	18, 19, 122, 123
Protein-calorie malnutrition	21
Other significant endocrine and metabolic disorders	23
End-stage liver disease; cirrhosis of liver	27, 28
Chronic pancreatitis	34
Rheumatoid arthritis and inflammatory connective tissue disease	40
Severe hematological disorders	46
Iron deficiency or other/unspecified anemias and blood disease	49
Drug/alcohol psychosis or dependence	54, 55
Psychiatric comorbidity	57-59, 61, 63
Hemiplegia, paraplegia, paralysis, functional disability	70-74
Seizure disorders and convulsions	79
Coronary atherosclerosis or angina, cerebrovascular disease	89, 102, 105
Chronic obstructive pulmonary disease	111
Fibrosis of lung or other chronic lung disorders	112
Viral and unspecified pneumonia, pleurisy	116
Kidney transplant status	132
Renal failure	136-139

Appendix Table A3. Descriptive Statistics for TM and MA Admissions by Condition, 2007-2014

	AMI		HF		PN		NTC	
	TM	**MA**	**TM**	**MA**	**TM**	**MA**	**TM**	**MA**
Index Admissions, N	268,932	139,528	661,673	274,527	502,650	176,226	8,738,244	3,733,952
Readmissions, N (%)	50,075 (18.6%)	23,420 (16.8%)	155,010 (23.4%)	58,454 (21.3%)	90,257 (18.0%)	28,317 (16.1%)	1,285,879 (14.7%)	492,007 (13.2%)
Age, Median (IQR)	79 (72-86)	78 (71-84)	82 (75-87)	80 (74-86)	81 (74-87)	80 (73-86)	79 (72-85)	77 (71-84)
Female, N (%)	133,016 (49.5%)	65,060 (46.6%)	360,970 (54.6%)	141,730 (51.6%)	272,715 (54.3%)	92,296 (52.4%)	5,055,533 (57.9%)	2,097,537 (56.2%)
# Comorbidities, Mean (SD)	1.51 (1.11)	1.39 (1.07)	1.82 (1.12)	1.67 (1.09)	1.72 (1.12)	1.57 (1.09)	1.52 (1.14)	1.40 (1.10)
Length of stay, Median (IQR)	4 (3-8)	4 (2-7)	4 (3-7)	4 (2-6)	5 (3-7)	4 (2-6)	4 (2-6)	3 (2-6)
Race (uniform), N (%)								
White	202,619 (76.2%)	94,211 (68.2%)	470,794 (71.8%)	171,245 (62.8%)	375,114 (75.5%)	121,283 (69.4%)	6,425,989 (74.4%)	2,405,175 (65.0%)
African-American	16,064 (6.0%)	12,597 (9.1%)	63,860 (9.7%)	41,670 (15.3%)	29,581 (6.0%)	15,670 (9.0%)	663,957 (7.7%)	442,961 (12.0%)
Hispanic	27,620 (10.4%)	21,322 (15.4%)	76,678 (11.7%)	41,981 (15.4%)	55,658 (11.2%)	26,054 (14.9%)	930,097 (10.8%)	588,821 (15.9%)
Asian/Pacific Islander	10,335 (3.9%)	4,940 (3.6%)	24,169 (3.7%)	8,776 (3.2%)	23,063 (4.6%)	6,780 (3.9%)	347,678 (4.0%)	131,812 (3.6%)
Native American	498 (0.2%)	181 (0.1%)	1,385 (0.2%)	373 (0.1%)	949 (0.2%)	227 (0.1%)	16,530 (0.2%)	4,857 (0.1%)
Other	8,686 (3.3%)	4,833 (3.5%)	18,484 (2.8%)	8,570 (3.1%)	12,392 (2.5%)	4,669 (2.7%)	256,573 (3.0%)	125,610 (3.4%)
Patient Location, N (%)								

Large Metro (>=1,000,000)	164,112 (61.2%)	111,303 (79.9%)	425,515 (64.4%)	224,406 (81.8%)	307,020 (61.2%)	139,070 (79.0%)	5,694,990 (65.3%)	3,054,071 (81.9%)
Small Metro (<1,000,000)	80,750 (30.1%)	23,768 (17.1%)	184,562 (27.9%)	42,559 (15.5%)	149,765 (29.9%)	31,147 (17.7%)	2,410,228 (27.6%)	582,455 (15.6%)
Micropolitan	16,975 (6.3%)	3,174 (2.3%)	36,598 (5.5%)	5,337 (1.9%)	31,283 (6.2%)	4,039 (2.3%)	444,813 (5.1%)	69,123 (1.9%)
Not metropolitan or micropolitan	6,392 (2.4%)	1,052 (0.8%)	13,996 (2.1%)	1,950 (0.7%)	13,503 (2.7%)	1,731 (1.0%)	168,044 (1.9%)	23,588 (0.6%)
Median Income by County, N (%)								
Quartile 1 (Poorest)	67,759 (25.8%)	34,960 (25.5%)	177,915 (27.5%)	74,056 (27.5%)	128,212 (26.0%)	41,826 (24.2%)	2,092,955 (24.5%)	930,926 (25.4%)
Quartile 2	70,274 (26.7%)	36,261 (26.4%)	169,060 (26.1%)	70,056 (26.0%)	132,306 (26.9%)	46,031 (26.6%)	2,167,467 (25.4%)	950,157 (25.9%)
Quartile 3	64,066 (24.4%)	36,870 (26.9%)	156,321 (24.1%)	70,298 (26.1%)	119,958 (24.4%)	47,668 (27.5%)	2,128,038 (24.9%)	973,766 (26.6%)
Quartile 4	60,897 (23.2%)	29,143 (21.2%)	144,490 (22.3%)	55,311 (20.5%)	111,718 (22.7%)	37,658 (21.7%)	2,154,181 (25.2%)	809,279 (22.1%)

Appendix Table A4. Descriptive Statistics for TM and MA Admissions by State, 2007-2014

	CA		FL		NY	
	TM	**MA**	**TM**	**MA**	**TM**	**MA**
Observations, N	4,090,666	1,994,928	4,069,295	1,544,690	3,403,050	1,318,655
Unique Patients, N	1,883,507	1,027,078	1,431,538	597,956	1,217,545	502,669
Age, Median (IQR)	79 (72-85)	78 (72-85)	79 (72-85)	77 (71-83)	80 (73-86)	77 (71-84)
Female, N (%)	2,310,343 (56.6%)	1,096,602 (55.0%)	2,282,556 (56.1%)	835,660 (54.1%)	1,997,725 (58.7%)	747,488 (56.7%)
# Comorbidities, Mean (SD)	1.59 (1.16)	1.42 (1.09)	1.58 (1.15)	1.46 (1.12)	1.45 (1.12)	1.40 (1.10)
Length of stay, Median (IQR)	4 (2-6)	3 (2-5)	4 (2-6)	3 (2-6)	4 (2-7)	4 (2-7)
Race (uniform), N (%)						
White	2,667,523 (66.6%)	1,348,737 (68.6%)	3,298,473 (81.4%)	1,006,294 (65.5%)	2,497,922 (73.7%)	773,899 (58.9%)
African-American	242,000 (6.0%)	138,135 (7.0%)	304,301 (7.5%)	203,569 (13.2%)	356,275 (10.5%)	244,112 (18.6%)
Hispanic	626,873 (15.6%)	318,977 (16.2%)	361,539 (8.9%)	282,164 (18.4%)	264,349 (7.8%)	162,228 (12.3%)
Asian/Pacific Islander	369,806 (9.2%)	130,411 (6.6%)	20,418 (0.5%)	7,575 (0.5%)	71,461 (2.1%)	32,589 (2.5%)
Native American	5,024 (0.1%)	1,846 (0.1%)	3,314 (0.1%)	1,228 (0.1%)	13,865 (0.4%)	3,312 (0.3%)
Other	89,373 (2.2%)	26,316 (1.3%)	62,088 (1.5%)	36,153 (2.4%)	184,814 (5.5%)	98,158 (7.5%)
Patient Location, N (%)						
Large Metro (>=1,000,000)	2,858,530 (70.3%)	1,713,752 (86.1%)	2,217,830 (54.5%)	1,121,398 (72.6%)	2,457,822 (72.3%)	1,137,142 (86.3%)
Small Metro (<1,000,000)	1,040,749 (25.6%)	268,212 (13.5%)	1,511,995 (37.2%)	376,684 (24.4%)	630,256 (18.5%)	112,985 (8.6%)
Micropolitan	113,950 (2.8%)	3,995 (0.2%)	254,539 (6.3%)	39,027 (2.5%)	226,381 (6.7%)	47,659 (3.6%)

Not metro or micropolitan	54,317 (1.3%)	3,590 (0.2%)	84,762 (2.1%)	7,454 (0.5%)	86,993 (2.6%)	20,450 (1.6%)
Median Income by County, N (%)						
Quartile 1 (Poorest)	1,055,657 (26.3%)	385,285 (19.6%)	1,078,017 (26.9%)	472,007 (30.9%)	689,409 (21.0%)	362,866 (28.6%)
Quartile 2	997,389 (24.9%)	476,205 (24.2%)	1,088,942 (27.2%)	438,609 (28.7%)	797,072 (24.2%)	323,460 (25.5%)
Quartile 3	1,005,052 (25.1%)	568,438 (28.9%)	999,941 (25.0%)	352,796 (23.1%)	796,920 (24.2%)	344,215 (27.1%)
Quartile 4	952,148 (23.7%)	539,614 (27.4%)	840,590 (21.0%)	265,630 (17.4%)	1,006,479 (30.6%)	239,587 (18.9%)

Appendix Table A5. Difference-in-Difference-in-Differences Results by Condition, 2007-2014*

	AMI	HF	PN						
	Coef	**SE**	**P Val**	**Coef**	**SE**	**P Val**	**Coef**	**SE**	**P Val**
Target	0.0416	0.0018	0.000	0.0728	0.0014	<0.001	0.0236	0.0013	<0.001
Post	-0.0053	0.0007	0.000	-0.0055	0.0007	<0.001	-0.0055	0.0007	<0.001
Target*Post	-0.0104	0.0022	0.000	-0.0049	0.0019	0.010	0.0000	0.0018	0.986
TM	0.0159	0.0007	0.000	0.0160	0.0007	<0.001	0.0159	0.0007	<0.001
Target*TM	0.0022	0.0020	0.268	0.0063	0.0015	<0.001	0.0038	0.0014	0.009
TM*Post	0.0016	0.0006	0.013	0.0017	0.0007	0.010	0.0016	0.0007	0.012
Target*Post*TM	-0.0009	0.0027	0.742	-0.0019	0.0022	0.388	-0.0041	0.0022	0.058
Age	0.0012	0.0000	0.000	0.0010	0.0000	<0.001	0.0011	0.0000	<0.001
Weekend Admit	0.0038	0.0003	0.000	0.0043	0.0003	<0.001	0.0038	0.0003	<0.001
# Comorbidities	0.0226	0.0003	0.000	0.0220	0.0003	<0.001	0.0223	0.0003	<0.001
Female	-0.0138	0.0003	0.000	-0.0138	0.0003	<0.001	-0.0145	0.0003	<0.001
Location (Large Metro ref group)									
Small Metro	-0.0102	0.0015	0.000	-0.0101	0.0015	<0.001	-0.0100	0.0015	<0.001
Micro	-0.0119	0.0019	0.000	-0.0117	0.0020	<0.001	-0.0113	0.0019	<0.001
Not Metro/Micro	-0.0175	0.0019	0.000	-0.0175	0.0020	<0.001	-0.0167	0.0020	<0.001
Race (White ref group)									
Black	0.0189	0.0008	0.000	0.0187	0.0008	<0.001	0.0190	0.0008	<0.001
Hispanic	0.0038	0.0007	0.000	0.0045	0.0007	<0.001	0.0031	0.0007	<0.001
Asian/Pac Islander	-0.0028	0.0011	0.009	-0.0025	0.0011	0.020	-0.0039	0.0011	<0.001
Native American	0.0115	0.0041	0.005	0.0100	0.0041	0.014	0.0091	0.0041	0.026
Other	-0.0090	0.0015	0.000	-0.0085	0.0015	<0.001	-0.0091	0.0015	<0.001
Median Income (Q1 lowest, ref group)									
Q2	-0.0038	0.0006	0.000	-0.0040	0.0006	<0.001	-0.0038	0.0006	<0.001
Q3	-0.0071	0.0006	0.000	-0.0071	0.0006	<0.001	-0.0070	0.0006	<0.001

Q4	-0.0108	0.0007	0.000	-0.0107	0.0007	<0.001	-0.0107	0.0007	<0.001
Year	-0.0006	0.0001	0.000	-0.0006	0.0001	<0.001	-0.0006	0.0001	<0.001
State (California ref group)									
Florida	0.0146	0.0016	0.000	0.0138	0.0016	0.000	0.0190	0.0015	<0.001
New York	0.0250	0.0004	0.000	0.0264	0.0004	0.000	0.0251	0.0004	<0.001

*The model also adjusts for hospital fixed effects

Appendix Table A6. Practice-Level Characteristics of Survey Respondents and Non-respondents

	Respondents (n=2,341)	Non-Respondents (n=2,704)	Sample Frame* (n=15,768)
Size			
% Small: 2-9 Physicians (n)	75.1% (1,757)	75.6% (2,044)	77.9% (12,279)
% Medium: 10-20 Physicians (n)	15.5% (363)	15.5% (418)	14.2% (2,232)
% Large: 21+ Physicians (n)	9.4% (221)	9.0% (242)	8.0% (1,257)
Mean # of Physicians† (SD)	11.8 (63.3)	10.1 (21.1)	9.6 (29.9)
Mean # of Primary Care Physicians (SD)	6.7 (12.3)	6.4 (7.6)	6.1 (8.0)
Mean # of Specialists (SD)	5.1 (51.8)	3.8 (15.0)	3.6 (23.4)
Mean # of Associate Providers‡ (SD)	2.2 (4.7)	2.2 (4.2)	2.1 (4.1)
Geography			
% Urban (n)	77.1% (1,804)	79.0% (2,136)	77.5% (12,215)
% Suburban (n)	15.9% (371)	15.4% (416)	15.5% (2,448)
% Rural (n)	7.1% (166)	5.6% (152)	7.0% (1,105)
% Midwest (n)	29.1% (682)	25.5% (690)	26.0% (4,096)
% Northeast (n)	20.0% (467)	20.9% (566)	20.5% (3,226)
% South (n)	26.5% (620)	30.0% (805)	32.0% (5,050)
% West (n)	24.4% (572)	23.8% (643)	21.5% (3,396)
System Characteristic			
% Independent (n)	32.5% (761)	35.1% (949)	48.4% (7,638)
% Medical Group Only System (n)	16.4% (383)	16.2% (438)	14.0% (2,206)
% Simple System (n)	15.7% (368)	14.0% (378)	11.8% (1,867)
% Complex System (n)	35.4% (829)	34.7% (939)	25.7% (4,057)
Mean # of Owner Subsidiaries (SD)	3.1 (5.9)	3.5 (6.4)	3.3 (6.4)
Mean # of Acute Care Hospitals (SD)	15.9 (33.3)	17.1 (35.5)	17.1 (37.7)
Mean # of Medical Groups (SD)	105.7 (147.0)	113.4 (157.9)	115.5 (160.8)
Mean # of states operating in (SD)	3.5 (5.7)	3.7 (5.8)	3.8 (6.4)
% Part of Medicare ACO (n)	30.8% (487)	32.3% (567)	28.9% (2,355)

*Includes surveyed and non-surveyed organizations
†Physicians = All MD/DO; Sum of Primary Care and Specialist Physicians
‡Associate Providers = Non-physician clinicians (e.g. NP, PA, CNS, etc.)

Appendix Table A7. Patient-Level Characteristics for Patients Attributed to Practices Responding and not Responding to Survey

	Respondents	Non-Respondents
Index Admission	415,663	6,035,536
Mean Age	77.8	77.9
Female (%)	56	56
Race (%)		
White	90	86
Black or Hispanic	7	10
Asian	3	4
Mean CMS-HCC score	2.8	3
Mean Length of Stay	4.7	5.0
Discharge Disposition (%)		
Home	48	44
Skilled Nursing Facility	25	22
Home Health	20	21
Original Reason for Entitlement Code (%)		
Old Age	85	84
Disability/ESRD	15	16
Dual-Eligible (%)	17	22
Median Household Income (IQR)	$58,497	$56,205

Appendix Table A8. Full List of Candidate Variables for Composite Measure

Does your practice have a system in place to routinely screen patients for:

	Yes	No
Low health literacy	☐	☐
Food insecurity	☐	☐
Housing instability	☐	☐
Utility needs	☐	☐
Interpersonal violence	☐	☐
Transportation needs	☐	☐
Need for financial assistance with medical bills	☐	☐

For your complex, high need patients, how often:

	Never	Sometimes	Often	Always
Is a care manager involved in helping the patient coordinate care across clinicians	☐	☐	☐	☐
Is a care manager involved in helping the patient adhere to the care plan	☐	☐	☐	☐
Is a non-clinician *(e.g. health coach)* involved in supporting **health risk modification**	☐	☐	☐	☐
Is a non-clinician *(e.g. health coach)* involved in supporting **medication adherence**	☐	☐	☐	☐
Are patients stratified into different subgroups for targeted interventions	☐	☐	☐	☐

When your complex, high need patients are hospitalized, which of the following are routinely in place to facilitate their discharge?

	Yes	No
Referral to community health-related social services	☐	☐
Communication with patient within 72 hours of discharge	☐	☐
Home visit after discharge	☐	☐
Discharge summaries sent to primary care clinician within 72 hours of discharge	☐	☐
Standardized process to reconcile multiple medications	☐	☐

Does your practice use any of the information below for internal use/quality improvement efforts targeting complex, high need patients?

	Yes	No
Hospital admissions or readmissions	☐	☐
Emergency department use	☐	☐
Medication adherence	☐	☐

Has your practice used the information above to make Modifications to the discharge planning process:

☐ Yes
☐ No

Does your practice collect patient-reported measures of Patient activation (e.g. self-efficacy for chronic disease mgt)

☐ Yes
☐ No

Considering the physicians and staff in your practice, how many:

	None	Some	Most	All
Routinely engage in shared decision-making	☐	☐	☐	☐

How often do clinicians in your practice have access to the following when they need it?

	Never	Sometimes	Often	Always
Notification that a patient was admitted to a local hospital	☐	☐	☐	☐

Does your practice manage information about individual clinician performance for internal quality improvement on use of acute care services *(e.g. readmissions, emergency room use)*:

☐ Yes
☐ No

Does your practice currently use any culturally tailored programs or interventions? *For example, a practice might provide culturally tailored programming to address preventive services in the Hispanic community with bilingual community health workers.*

☐ Yes
☐ No

Appendix Table A9. Mixed Effects Logit Model of Patient-Level Readmission Rates

	Odds Ratio	SE	P Val
Fixed Effects, N=415,663			
Race (ref. group white)			
Black	0.967	0.017	0.067
Other	0.967	0.026	0.214
Median Income	0.999	0.000	0.008
Frailty	1.071	0.003	<0.001
HCC Score	1.483	0.004	<0.001
Random Effects			
Practice var(_cons), N=2,073	0.046	0.004	

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